



**IDENTIFYING CUSTOMER SEGMENTATION MODELS FOR FINTECH & FINDING
THE CONSUMER BEHAVIOURAL DIFFERENCE THROUGH A STUDY OF PAYMENT
INSTRUMENTS & E-COMMERCE IN INDIAN MARKET**

by

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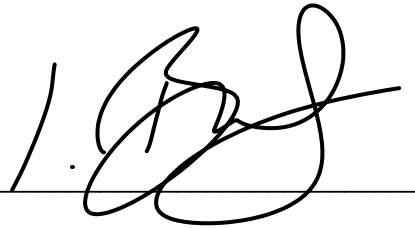
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Dedication

I would like to dedicate this thesis to my family especially my wife who has been a pillar of support and helped me stand strong mentally throughout the last three years. I would also like to thank my parents and kids for being the eternal supporter of my cause.

Acknowledgements

I would like to thank my mentor Dr. Aaron Nyanama for providing the coaching and right guidance throughout the DBA journey.

ABSTRACT

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2024

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Background

The Advent of Fintech payment instruments has led to significant discussions around customer shifts from Credit cards to Fintech products especially BNPL and UPI, both for E-commerce & POS. This discussion has been the focus point of various industry reports considering the meteoric increase in payment methods innovations, investments, and number of companies. With limited academic research to fully understand this difference across the world, there exists a gap in defining the finite customer segmentation for various payment instruments. As per the extensive research done by the author, this study is one of the first such research in Indian geographical limits. Additionally, the impact of these fintech products on E-commerce consumer behaviour and an understanding of differentiated customer segmentation for E-commerce with an absolute vacuum for Indian territory.

Methods

This research has used K-Means Clustering & Hierarchical Clustering for the identification & classification of principle variables for the payment Instruments & E-commerce. PLS-SEM is used to understand the relationship strength between these variables and validate the model proposed.

Results

Trust, Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions are found to have strong impact on the customer purchase intentions using all digital payment mode.

Payment Preference of a customer strongly affect all the above parameters in addition to having a strong impact on customer purchase behaviour. The study found a strong impact of rewards and discounts on customer Purchase intentions and choice of payment methods. Tech attributes like widespread availability, UI/CX, merchant acceptance, 1-click payment, ease of payment, and high security features have a strong impact on customer payment preference and indirect effect on customer purchase intentions. Payment Preference is also affected by government policies and geopolitical factors who have significant indirect effect on customer purchase intention. Demographic factors Age, Gender, and Income, along with Type and value of purchase also impacts choice of payment method differently. While Credit Card and Digital Wallet uptake increases with increase in Age and Income, there exist a negative relationship between BNPL and Debit Card / Internet banking with Age and Income.

Discussion and Conclusion

During the process, the research also creates the first true academic framework for Payment method customer segmentation from an Indian perspective which can also be replicated across other geographies. The author proposes a STATE model for gauging the impact of payment methods on E-commerce comprising of Service Benefit Expectations, Type of Customer, Attributes of Tech, Type of Purchases, and External Factors and communication.

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CHAPTER1: INTRODUCTION

1. INTRODUCTION

1.1. E-commerce & Payment Instruments:

The key to success for any E-commerce & POS company is to identify the right customer base for their product. A higher purchase intention arises for the customer when provided with the rightly segmented product with appropriate communication and expected payment instruments.

Additionally, the payment & credit lending solutions are typically provided by either banks, Fintech or standalone credit card companies. The customers are likely to choose one of these methods based on their need, comfort and availability. In absence of the right payment product, there is high likelihood of a customer to abandon his cart. The research by Brophy & Aviso (2022) suggests that 9% of the customers drop out due to unavailability of preferred payment method and 17% move out due to convoluted checkout and payment process. The report also suggests that 48% of the users consider cost to be the reason for not availing cart. Providing the preferred payment solution and meeting the latent credit requirements leads to significant increase in cart conversion rate.

As per Bluesnap & Splitit (2022), there is largescale checkout abandonment happening wherein the customer leaves at the point of checkout without closing the purchase. This is more painful for the retailers as customers have done all the hard work and have left towards the end of the sales cycle. The most important reason for checkout drop-off is again absence of required payment process.

For POS (Point of Sale) transactions too, customers end up with a lower basket value or leave the product due to limited or inadequate availability of financing & instalments options, no Credit card payment option, and absence of preferred fintech player to choose from. The above studies signify the importance of payment & lending products and getting the right solutions to amplify the conversion both for E-commerce & POS.

The rise of E-commerce and payment options over the last two decades have completely revolutionized the online & offline shopping pattern for the customers. Fintech has become a great tool for customers to experience purchases, avail credit and pay via multiple alternate channels of their choice. Now customers are using products like BNPL (Buy Now, Pay Later), Digital Wallets, Digital lending in addition to credit cards & Personal loans to enhance their basket size. This is a huge win-win for retailers, as customer's purchasing power and propensity has increased exponentially with implementation of these products. The prominent pointer is the continuous innovations in Fintech & Payments sector which is minting unicorns at an unabated pace across the world. The growing customer onboarding for digital products has also led to increased financial penetrations in remote & underbanked areas and segments, which in turn is contributing to greater financial inclusiveness across classes and geographies.

There has been a rapid digitalization and uptake of digital payment methods which is further sprinted due to the pandemic and commensurate movement restrictions cause by it. One of the most noteworthy stories is the rise of the BNPL. A report by C+R Research (2021) finds out that 71% of the customers are using E-commerce more during pandemic and 51% of the respondents confirmed using BNPL during the pandemic.

The exponential rise of Fintech has also led to companies in payments & lending ecosystem fighting for the highest share of wallet (both in digital & physical space, commonly termed as Physital) of the customer. For eg., a BNPL company is not only competing with various other BNPL players but also with Credit Card companies, Super Apps, Digital lenders, Personal loans, Wallets and cash. Similar is the story for all other companies and products in this space.

With increased competition and new innovations, companies are working overtime to create unique solutions for the customers. To achieve this, marketers are using various customer acquisition strategies including WOM (Word of Mouth), Niche & Micro Marketing (Kotler, 2022), Relationship marketing, Inorganic acquisitions through offers & discounts, among many more. This is done through understanding the factors affecting purchases, assessing customers intrinsic & extrinsic needs, as well as by increasing the distribution and marketing strength; in short segmenting customers into cohorts, personas & groups based on Demographic, Behavioural, Psychographic, Geographical, RFM, and a combination of these among others.

There has been huge number of research which has been done in the field of online shopping & purchase behaviour (Kotler, 2022; Lin et al., 2004; Kara & Kayanak, 1997; Peppers and Rogers, 2015; Yelkur and DaCosta, 2001; Belvaux and Guibert, 2012; Ul Islam et al., 2017; José Liébana-Cabanillas et al., 2014; Broitman et al., 2021; Klarna, 2020 among others).

1.2. Indian Fintech Market

From an Indian context, there has been very limited academic research done in BNPL & Fintech segment. As per BCG (2022), India has been rapidly growing with highest CAGR of 20% in Fintech and is currently ranked at 3rd position in terms of size. Similar to other parts of the world, Indian Fintech companies are also witnessing stress with 58% of the companies reported shrinking EBIDTA margins. (44% also reported fall in growth). The report also points out that BNPL, Cards & unsecured lending are the area which most likely to be disrupted with new innovations. Another study by Srinivas & Prasad (2022) suggests that while BNPL provide an easy access to credit, there are multiple costs associated with it both pre & post approval of limit. The report also highlights the possibility of high value impulse purchases which might push customers to debt trap.

1.3. Research Area

The absence of a clear customer & product segmentation in Fintech has led to a chaotic market situation wherein everyone is competing for every customer. This has led to huge stress in the market and most of the new age fintech companies are either losing customers or growing on top of inorganic acquisitions through offers and discounts, funded by investors money (Berr, 2022).

This study focuses on Fintech Marketing and customer segmentation across different product class to understand the difference in customer requirements & expectations, and further identify the gap for new niche development.

The focus area of this study is Indian Payment Instrument, and Fintech market. The BNPL segments varies significantly based on Geography (RFI, 2022), Behavioural and Psychographic attributes.

1.4. PROBLEM STATEMENT

1.4.1. OVERVIEW

Currently, E-commerce segmentation has been done using Demographic, purchase History, Behaviour, Psychographic by Baer (2012), Collica (2011) & Magento (2014). Recently, various research in this field has been conducted using structured and unstructured data using clustering techniques along with focus on RFM and loyalty parameters to ascertain the customer personas and segments. Additionally, there are various other research conducted for Fintech customers which were mainly focused on Generational segmentations and use of Technology. There is a gap in academic understanding of customer segmentation behavioural difference between a pure e-commerce customer vs one using the Fintech.

Fintech sector with interest from both researchers and corporate, has turned the wheel by decades and become ultra-focused on product differentiation (to alter the demand at the will of the supply) as discussed by Smith (1956). Most companies try to understand the market, identify the gap and create a product driven marketing strategy, wherein the buyers expect customers across segments to use these products based on their features. This product based, or at best customer response-based development comes with a huge scope for failure. Another major gap with Fintech companies is that they assume the Fintech customers to respond in similar way to an E-commerce customer. While, there are lot of synergies and similarities between them, there is a good possibility of customer behaviour varying significantly in terms of Fintech and the E-commerce. The Fintech are being considered as part of banking system and have high legality quotient, far more compliant and are heavily regulator driven vis-a-vis E-commerce (Wilson & Rosati, 2022). But Marketers have for long missed this point and used the E-commerce customer segmentation to Fintech too. With the advent of Hybrid & Neural segmentation, there is a definite possibility of getting a clear demarcation of Customer segmentation difference between the E-commerce and the Fintech & banks.

Additionally, there is limited research available on customer segmentation differences between the various products like Digital lending, Digital Wallet, BNPL, Credit Cards, Banks & Personal loan. There is a huge gap in understanding of target segments for different Fintech products and many a times, Fintech products are segmented and positioned as replacement for conventional banking products. One of the good examples of this is the target segments for BNPL. BNPL (Buy Now Pay Later) is touted to help provide access to credit to a much larger segment and currently it is being discussed as an alternative to Credit Card or Personal loan (Srinivas & Prasad, HDFC Securities, Zest Money, McKinsey). While companies have started providing BNPL as an offering across various segments, there is still a huge ambiguity in terms of target market & customer segmentation. There has been a huge interest in this field and investments have also increased multi fold in this sector. With demarcated customer segmentation, companies & governments can use BNPL as a tool to pull millions out of poverty and provide them access to credit & consumerism.

BNPL (Buy Now Pay Later) is age old phenomenon dating back to the formal merchant system much before Christ. It was as a short-term credit being issued by merchants & local traders to buyers based on trust and understanding. Khata system was and is extremely popular in India. Postponed payments in Europe were popular around 19th century. EMI and installments have been the most popular lending method. BNPL is another variation on similar concept with technology as the major underlying architecture and is on the rise across the world with India as one of the leading markets for it. According to the report by Zest Money (2022), there is a 500% growth in user in last two years in BNPL while credit card usages are on a decline across major countries. Buy in 3, Pay later, pay in installments schemes have been on a rise thanks to the POS & online sales through BNPL solutions.

The report further states that BNPL users to exceed Credit card users in the market by 2026.

There is a general discussion in the Fintech industry about BNPL, Credit Card, Personal loans being supplementary products and rise of one will lead to demise of others. As per report by *the financial brand - Google Zoeken* (2021) suggest that credit card faces an existential crisis from the rise of

BNPL and 52% of the users are happy to replace the credit card with a BNPL product.

The BNPL is also getting a lot of attention thanks to its seamless integration at POS & Embedded commerce as well as rise of Super apps like Klarna, Affirm, Tata Neu, Alipay among others. As per Zest Money (2022), the BNPL & D2C are a true match with lot of attention during the Covid & post covid times with 10X growth for the brands who enabled zest money BNPL solution at checkout. According to another research by Bain, BNPL penetration is expected to increase from 5% to 25% in next few years with the brands employing embedded E-commerce at its core.

This brings a lot of gaps witnessed in the current understanding and academic research in this field. There is very little academic research to understand the BNPL and other payment product markets and their impact on the Fintech and e-commerce industry. There is also a gap in clarity on who is the real customer for credit cards, BNPL, and other payment products in the market. Additionally, there is a gap in understanding of differentiation in customer segmentation for E-commerce pre & post-BNPL and other payment method implementation.

At the same time, products like Alternate credit score-based financing & BNPL lure has also led to significant increase in stress for end users with mounting credit and possibility of debt trap for a majority of them. A study by Guttman-Kenney et al. (2022) suggests that 19.5% of the customers are billing their BNPL transactions to credit card. This shows a systematic red flag as revolve rate for credit cards are upwards of 20% and it questions the borrower's overall capacity to pay back. Another report by HDFC Securities (2022), the current vanilla BNPL cost calculations with existing structure suggest an unviable business model with higher credit cost for Fintech companies leading to overall loss for the business in India.

Above discussions suggest to an ambiguity over the BNPL & other Fintech segmentation. With very limited academic research in this field, a detailed study is required to understand the gap in the

customer segmentation. This research aims to identify the right customer base for all E-commerce and Fintech products to help the marketers understand the target segmentation. Another rationale for undertaking this study is to create a framework for segmented customer outreach for various fintech products in India. As per the research by Bagnall et al (2014), the choice of payment method varies significantly from one country to another due to cultural and policy differences. In the process, the study also aims to find a profitable target market for BNPL products. This will lead to huge opportunities for product development and niche marketing for BNPL customers which shall also help to bring a lot of calmness in the product that has seen tremendous stress due to decreased margins and ballooning losses.

1.5. RESEARCH QUESTION

The current study aims to answer these questions:

1. Is there a modifying effect of Digital payments on E-commerce Behavioural intention to purchase in India?
2. Does different Fintech payment instruments and methods impact e-commerce usages differently
3. Are customers using multiple payment instruments simultaneously in India?
4. Do consumer behavior and customer segmentation impact multiple payment methods usage and alternative switching between payment instruments in India?

1.6. OBJECTIVES AND AIMS

1.6.1. OVERALL OBJECTIVE

The main objective of this study is to provide a comprehensive understanding of Fintech payment instruments customer segmentation in India and identify the right segmentation for BNPL.

1.7. SPECIFIC AIMS

1. To understand the behavioural difference between fintech payment instruments and E-commerce customers and understand the impact of these instruments on E-commerce transactions in India
2. To provide a framework for choice of payment method in India
3. To understand the difference of customer segmentation between choice of payment method and their difference in consumer behaviour and segments.
4. To identify niche customer segments for various payment methods including CC, DCIB, DW, UPI, BNPL, and COD in India which is a win-win for all stakeholders including Retailers, BNPL players, regulators, and without putting additional stress to end users and to check if Islamic Fintech can be one of the niche segments for BNPL.

1.8. BACKGROUND AND SIGNIFICANCE

This is a highly significant study with many implications. Unlike previous studies already done on this topic, this study expands the current body of empirical studies already done on understanding and segmenting E-commerce, Digital Lending, Digital Wallet, Credit Cards & Personal Loan individually in India by applying different approaches. The significance of this study also lies in the fact that it does not only seek to examine the relationship between to understand the difference in customer segmentation between the choice of payment method and their difference in consumer behavior and segments, but it also seeks to do so in India, an

emerging economy whereas previous studies were mainly done in developed countries in Europe and America. This is significant in the sense that findings from this study could help guide the decisions of e-commerce business owners when contemplating on how to segment customers. Findings from this study could also expand the body of research on why some e-commerce businesses do well while others don't. Additionally, results could benefit future entrepreneurs, especially start-up e-commerce businesses seeking to avoid difficulties associated with the lack of understanding of local e-commerce behavior in India.

There has been various research on the E-commerce customer segmentation as discussed earlier and similar is the case for consumer behaviour in choice of payment methods. While the previous researches were focusing on limited impact of payment instrument on E-commerce customer behaviour, there is a gap in understanding the behavioural gap between E-commerce and Fintech. With lot of discussions around BNPL overtaking credit card and other lending products, I found it an urgent requirement to identify the right customer segmentation for various fintech products.

CHAPTER 2: REVIEW OF THE LITERATURE

2. LITERATURE REVIEW

2.1 CUSTOMER SEGMENTATION

Though the idea of customer segmentation existed since ages, a formal shape to it can be attributed to 19th century with the idea of Fragmentation as a marketing strategy. A structured attribution is given to Smith (1956) This was the first time Market segmentation was officially used as a marketing tool. It talked about segmentation as “a marketing strategy based upon development on demand side of the market and a ration to adjustment in product as per the demand side requirements. Yankelovich (1964) discussed in detail about two commonly used segmentation methods: Value segmentation wherein the perceived value as well value requirement led to segments; and the Need based segmentation.

Customer and market segmentation’s commonly used models are Demographic, Geographic, Behavioural & Psychographic segmentation which is widely used to understand the market & customer (Agrawal, 2021).

2.1.1. DEMOGRAPHIC SEGMENTATION

Demographic segmentation deals with factors like Age (Barat, 2010), Gender (Wyly & Ponder, 2011; Klarna, 2020), Religion, Family size, ethnicity, Occupation, education, Income (Bauer & Auer-Srnka, 2012) etc. As per Metawa et al (2019), Gender, Age, and education has an impact on Invest decisions by the customers. This has been the market segmentation pillar for decades as this is also the easiest and generally directional segmentation method. With availability of data through Social & connected mediums, this segmentation method has been widely applied on big data for market research to great degree of success. This segmentation is hugely successful in creating focused campaigns and advertisements (Agrawal, 2021).

2.1.2. GEOGRAPHIC SEGMENTATION

Geographic segmentation is done basis the locality, nationality, city, state, pincode among others. For similar demographics, customer's location plays a key role in defining the interest. Few of the influencing factors for this are community effect, policies & processes being followed by the respective government, access to technology & exposure among others (Agrawal, 2021).

While demographic segmentation is still the first base to begin with, a deeper segmentation is required as customers with similar demographics show varied behavior and attitude towards a purchase decision.

2.1.3. BEHAVIOURAL SEGMENTATION:

Yankelovich (1964) suggests that sex, gender & age can't be the relying factor for segmentation and suggested use of non-demographic factors for market research. While customer's demographics and geographic details are externally visible and available; for similar attributes of both, the customer's behaviour might vary based on the benefits sought from the product. These benefits are generally categorized in loyalty and affinity towards the product, brand or company, customer journey stage, purchasing behaviour, usage, engagement level, and occasion among others (Huseynov & Yildirim, 2017).

2.1.4. PSYCHOGRAPHIC SEGMENTATION:

Psychographic segmentation was coined by Emanuel Demby around the 60s (Wells, 1975) and during the same period, Mitchell (1978) introduced the famous VALS (Values, Attitude, & Lifestyles) way of segmenting the customers. The customer intrinsic personality traits, values, attention, Interest, opinion about the product, his social status, the day-to-day activities he is getting exposed to, all play a significant role in segmenting the customers. In fact, with social media & other data mining

companies getting access to customers need and expectations, certain insights about their lifestyle, values, companies are looking at identifying much finer micro segments to create the hyper personalization impact for their users.

2.1.5. GENERATIONAL SEGMENTATION:

Another famous segmentation method is Generational segmentation (Baby Boomers, Gen X, Gen Y or Millennial. GEN Z & Gen Alpha) by Schewe and Meredith (2004).

Generational segmentation is not a life stage segmentation method. It is used to denote people born within a historical time frame.

Other famous customer segmentation frameworks are RFM (Recency, Frequency, & Monetary) Analysis by Bult and Wansbeek (1995): NPS (Net promoter score) wherein customers are given scores between 1-10 for Detractor, Passive & Promoter. These scores are then measured on a scale of -100 to 100 (Reichheld, 2004). Perception based segmentation which is basically a post hoc method as compared to RBMS (Response based management system), predictive segmentation using computational models which helps in further breakdown of problem in finer micro segments like firmographic, Technographic, Hybrid segmentation and Personas (Cooper et al., 2007) and Communities with coherent identities by Jenkinson (1993).

2.1.6. PERSONAS

Personas are used extensively in customer segmentation especially with the availability of Bigdata (Stevenson & Mattson, 2019) to create imaginary personalities with similar buying pattern. Hybrid customer segmentation is one area of research which has much less focus and need more organized results. Additionally, the advent of hyper-personalization engines and CDP tools (Valdez Mendia &

Flores-Cuautle, 2022) have facilitated creation of personas and personalized communication a much more accessible task compared to earlier days.

In modern world, the fields of Biology, Psychology, Sociology, economics, IT & management have come together to create another unique way of using unbiased insights of consumer behaviour through Neuromarketing.

2.1.7. NEUROMARKETING

Neuromarketing as a word was coined by Smidts (2002) in early 21st century and popularized by Kahneman (2011) through his System 1 & System 2 theory. This has also been promulgated by Monatague (2004) with its ultra-famous Coke vs Pepsi experiment. Neuromarketing tries to understand the implicit requirements of the customer vis-a-vis explicit feedbacks. Neuromarketing is based on dual process theory with a difference in action between the unconscious and the conscious reasoning. Previous research undertaken by this author has shown the importance of ECR model (Emotional-Cognitive-Reactive) in decision making (Aggrawal, 2022). The research highlights the importance of Emotions in decision making and how it is connected to the fast/slow decision making. The ECR model also suggest that customer behaviour, emotions & decision making are impacted by various intrinsic (Neuro-signals, Brain pulse & response to stimuli, various Hormones, DNA, Blood Group, Physiological characteristics, Respiratory, Cardio-vascular, and Gastronomic processes) as well as external factors (Color, Anchoring, Audio & Visual stimuli, Velocity, Odour, Smell, Taste, Emotional Intelligence etc). This allows for the segmentation of customers based on user sensitivity to these factors. As per Cervalo et al. (2019) research based on fMRI sessions on sixteen customers, cash can act as a great self-regulating method as parting with cash result in negative emotional feeling. The study further highlights that parting with higher value of cash result in significantly higher negative emotions in the customer.

2.1.8. EMOTIONAL INTELLIGENCE

Emotional Intelligence is defined as ability to understand & manage self and other's emotions internally & externally (Goleman, 1995). Goleman's model defines EI into four segments based on recognition and regulation of emotions: Self Awareness (Emotional Self-awareness, Self-Assessment, Self-confidence), Social Awareness (Empathy, organizational Awareness, Service Orientation), Self-management (Self-control, Trustworthiness, conscientiousness, adaptability, Achievement drive, Initiatives), Relationship management (Influence, communication, Developing others, conflict management, leadership). There is a growing discussion on using Emotional Intelligence as a significant factor in consumer decision making & purchase behaviour. As per Kidwell et al. (2008), any person with higher Consumer Emotional Intelligence (CEI) can successfully use emotional information to achieve desired purchase outcome. Kotler et al (2010), Jewell et al. (2009) agrees to the significance of EI in consumer purchase decision.

2.2. MODELS FOR CUSTOMER SEGMENTATION WITH FOCUS ON DIGITAL PAYMENTS & E-COMMERCE

After a detailed customer segmentation review across different models, it can be deduced that no single method is sufficient to explain the customer behaviour across diverse groups, events and offerings. Having said that each of the models have been extensively used to explain customer behaviour across the world. The paper has discussed about various segmentation strategies for identifying the appropriate customer segments for marketers. In this section, the paper reviews specific segmentation techniques being employed by researchers to achieve the desired result.

2.2.1. RFM (RECENCY, FREQUENCY, MONETARY)

RFM is one of the widely used tool for behavioural segmentation of the customers based on customer transactional data (McCarty & Hastak, 2007). At times, RFM is combined with various algorithms for

identification of customer segments. Most common cohorts identified through this analysis are Champions, Loyal customer, Potential loyalist, Recent customers, Promising, Customer needing attention, about to sleep, at risk, can't lose them, Hibernating, Lost. (Pan, 2020)

LRFM (Reinartz & Kumar, 2000): Herein the Length of relationship is added to RFM analysis as cost of maintenance of relationship is low while there is a positive relationship on incremental monetary value with increased relationship length.

2.2.2. PERCEPTION BASED SEGMENTATION MODELS:

There are various segmentation models based on use of technology and decision making like TAM, TPB, IDT, TRA, UTAUT1, UTAUT2 (Technology Acceptance Model, Theory of Planned Behaviour, Innovation Diffusion Theory, & Theory of Reasoned Action, Unified Theory of Action and Use of Technology 1 & 2).

These models establish a connection between perceived external factors to attitude / behaviour and thus to intention to use. The first to develop was TRA by Ajzen & Fishbein (1975) which focused on the impact of attitude / behaviour on the adoption of technology.

2.2.3. S-O-R (STIMULUS – ORGANISM – RESPONSE)

One of the oldest consumers behavioural theories proposed by Woodworth (1929) which suggest the Response (Approach or avoidance) i.e., of any stimulus (Environmental or marketing) through the internal assessment of the individual including state of mind (Organism). This takes into account the response to stimulus on the attitude of the consumers which is not properly validated in other theories (Dzandu et al., 2020). S-O-R has been widely used in advertisement, campaigns, digital marketing for its simple yet decisive response outcome mechanism.

2.2.4. TRA (THEORY OF REASONED ACTION)

Theory of Reasoned Action is a scientific model for prediction of behaviour outcome through behavioural intention. The theory takes in account the Subjective Norm, Belief & Attitude of the individual towards a service or a product. Attitude is a direct response to behavioural belief and evaluation of these beliefs by the individual. Subjective norm is affected by perception of others about the action of individual and external factors. The TRA suggest that Subjective Norm is a function of Normative Belief (How a significant other believe that the person should be doing / not doing something) and Motivation to Comply (Ajzen & Fishbein, 1975).

2.2.5. TPB (THEORY OF PLANNED BEHAVIOUR)

The above theory was modified to create the Theory of Planned Behaviour (TPB) by Ickek Ajzen in 1985 wherein he added Perceived Behavioural control as another factor driving behaviour intention. Perceived Control is the belief of an individual that he or she can perform the given action successfully under the provided circumstances. The theory suggest that individuals are more likely to engage in behavioural action wherein they believe of a successful outcome or desired result.

2.2.6. SCT (SOCIAL COGNITIVE THEORY)

Social Cognitive Theory as defined by Albert Bandura (1977) and full developed by 1986, suggests that any individual behaviour is both affected by the environment as well as affects the environment. The theory shows the inter relationship of Cognitive, Behavioural and Environmental factors (Reciprocal Determination). There are six components for SCT which adds Self-efficacy over the Social Learning Theory proposed by Bandura in 1962. These components are Reciprocal Determination (Dynamic response of individual within an external social context in response to an external stimuli), Behavioural Capability (Actual ability to perform the goals), Observational Learning (Reproduction of behaviour through observation of others), Reinforcement (Continuance of

behaviour based on outcome), Expectation (Anticipated outcome of the behaviour), and Self-Efficacy (A person's confidence in the ability to perform a behaviour successfully).

2.2.7. TAM / TAM2 / TAM3

The widely used TAM was developed by Fred D. Devis in 1986 which originally added two external factors perceived ease of use and perceived usefulness. These variables affected attitude / behaviour towards the product which in turn impacted intent to use. TAM was further extended to TAM2 & TAM3 to add in the Subjective Norms. TAM2 identifies two factors social influence and cognitive instrumental. Social influence consists of subject norm, image, voluntariness & experience. Cognitive instrumental consists of job relevance, output quality & result demonstrability (Venkatesh & Davis, 2000). Subjective norms are perception of important people on mandatorily doing / not doing a task over and above the perceived usefulness. Subjective norms are positively correlated to image of the person while Voluntariness adds in the moderating factor. The experience indicate that the impact of the perception is highest in beginning of the task and decreases over time with increased system experience. Job relevance related to the perception of importance of a task to the work function while output quality denotes the efficacy of the systems performing the relevant job. Tangibility of the results will directly influence the perceived usefulness. TAM3 adds in various factors impacting perceived ease of use within two categories of Anchor and Adjustment. Anchor contains self-efficacy, perception of external control, anxiety, playfulness while adjustment is done through perceived enjoyment & objective useability. (Venkatesh, 2012)

The above theories discuss in detail about various important factors which help in segmentation for adaption of technology.

Few of the factors as per the TAM (Technology Acceptance Model) developed by Davis (1986) & TAM2 by Davis & Venkatesh (2000) are:

1. **Perceived Usefulness:** users are expected to incorporate any technology if they have a higher output expectation in terms of productivity and effectiveness due to this.
Naruetharadhol et al. (2022) identified that perceived usefulness is directly related to behavioural intentions.
2. **Perceived Ease of Use:** As per the TAM, users are more likely to use any technology if their effort perception to implement the same is low. In other words, how easy, customer find the use of any technology, higher the adoption rate
3. **Subjective Norm:** As per the TAM2, Subjective norm refers to the belief of individuals about people who are close to them doing / not doing any specific task. As per the scientists, subjective norm is a cumulative outcome of Injunctive Norm & Descriptive Norm. Injunctive Norm is people perception of what others believe that they should be doing. Descriptive Norm is people perception of what others are doing themselves.
4. **Voluntariness:** This factor refers to the perceived compulsion / free will in performing a task / adapting new ideas.
5. **Image:** This factor refers to the perceived value in the society by implementing any technology
6. **Experience:** This factor signifies the receding impact of subject norm with passage of time and additional learnings.
7. **Job Relevance:** This is one of the cognitive Influence factors where in adoption of technology depends on perception of extent of application in one's job
8. **Output Quality:** This factor indicates the expected quality of output as one of the factors for acceptance of technology
9. **Result Demonstrability:** Any innovation which result in tangible output has much higher chance of adoption

2.2.8. UNIFIED THEORY OF ADOPTION AND USE OF TECHNOLOGY (UTAUT)

The TAM & TAM2 while being hugely popular, were still unable to explain the reason for lack of use of technology. To overcome this challenge, Venkatesh et al. (2003) proposed a combined Adoption & usage model as Unified Theory of Adoption and Use of Technology (UTAUT) which is based on four constructs as detailed below: (Zahra et al., 2019)

1. Performance Expectancy: This factor discusses the perceived usefulness of technology to improve the performance at workplace
2. Effort Expectancy: This factor discusses the expected ease of use in usage of technology. A higher required effort leads to lesser use of technology
3. Social Influence: This factor takes into account the Subjective Norm in use of technology
4. Facilitating conditions: The use of technology is also impacted by the surrounding conditions like organizational policies, infra, & readiness which makes it easy for effective usage.

UTAUT is generally used with moderators to increase the explanatory attributes but this also leads to increase in complexity in implementation of model.

UTAUT2: Venkatesh et al. (2012) extended the model to better predict the behaviour intention and use of technology:

1. Hedonic Motivation: Does use of the technology in discussion leads to enjoyment and fun for the user.
2. Price Value: This deals with expected change in monetary requirements with use of technology
3. Habit: Does the use of technology become part of any routine for the use?

Also, there are various extension to UTAUT 2 model with additional variables to accommodate for specific technology or product.

2.2.9. ECM (EXPECTATION COMPETENCY MODEL)

ECM is a derived model based on Theory of Planned Behaviour and TAM which suggest that if Performance of the product is matched with Perceived Expectation, there is an increased adoption of technology. This is impacted by perceived usefulness and it in turn leads to satisfaction and continuance intention. (Bhattacharjee, 2001)

While the author agrees with the significance of TAM & UTAUT model in identifying adoption and usage behaviour of the product, a more detailed conceptual framework is proposed by the author by combining the UTAUT with the Emotional Intelligence & Neuromarketing model to fully explain the reason for preferential uptake of one technology over other.

2.2.10. IDT (DIFFUSION OF INNOVATION)

As detailed by Rogers et al. (1962, 2019), Diffusion of innovation (DOI) tries to identify the pace of the adoption of any new innovation through factors like Innovation, Communication channel, Social system, and Time. Innovation is any idea, object or practice which is perceived as new by an individual, group or organization. It is affected by six distinct identifiers of Innovation; namely: Complexity, Adaptability, Compatibility, Relative advantage, Trialability & Observability. The IDT theory proposes that through communication channels, the idea is diffused to larger audience over a period of time. It categorizes people as Innovators, Early adopters, Early majority, Late majority, and Laggards based on the speed of embracement of innovation.

2.3. SUMMARY OF CUSTOMER SEGMENTATION ATTRIBUTES DETAILED BY VARIOUS AUTHORS:

Behavioural & Demographic segmentations were initially the most driving customer segmentation models. With advent of technology & BIG DATA, a combination of models has been used to predict the customer segments. These segments are generally a mix of response-based segmentation models and perception based segmentation models.

Table 1: Customer Segmentation

Author	Year	Variables / Factors / Attributes	Segmentation	Type of Segmentation
Barat	2010	Age	Demographic	Response based Segmentation Model
Klarna	2020	Gender	Demographic	Response based Segmentation Model
Wyly & Ponder	2011	Gender	Demographic	Response based Segmentation Model
Bauer & Auer-Srnka	2012	Income	Demographic	Response based Segmentation Model
Metawa et al	2019	Age, Gender & Education	Demographic	Response based Segmentation Model
Agrawal V	2021	City, Pincode, State, Nationality	Geographic	Response based Segmentation Model
Yankelovich, D.	1964	Loyalty, Purchasing behaviour	Behavioural	Response based Segmentation Model
Huseynov & Yildirim	2017	Engagement level, Usage, Purchasing behaviour, Customer Journey Stage	Behavioural	Response based Segmentation Model

Mitchell	1978	Values, Attitude, Lifestyle	Psychographic	Response based Segmentation Model
Schewe and Meredith	2004	GENX, GENY, GENZ	Generational segmentation	Response based Segmentation Model
Bult and Wansbeek	1995	Recency, Frequency, Monetary (RFM)	Behavioural	Response based Segmentation Model
Reichheld	2004	Detractors, Passive, Promoters (NPS - Net Promoter Score)	Behavioural	Response based Segmentation Model
Stevenson & Mattson	2019	Imaginary personalities based on cohort	Personas	Response based Segmentation Model
Valdez Mendia & Flores- Cuautle	2022	Database segmented cohorts through CDP	Personas	Response based Segmentation Model
Jewell et al.	2009	Self-Control, Self- Awareness	Emotional Intelligence	Response based Segmentation Model
McCarty & Hastak	2007	Transactional Data (RFM)	Behavioural	Response based Segmentation Model
Pan	2020	Customer cohorts based on RFM	Behavioural	Response based Segmentation Model
Reinartz & Kumar	2000	Recency, Frequency, Monetary & Length of relationship(LRFM)	Behavioural	Response based Segmentation Model
Azjen & Fishbein	1980	Attitude, Behaviour	TRA	Perception based Segmentation Model
Davis	1986	Perceived Ease of Use, Perceived Usefulness	TAM	Perception based Segmentation Model

Davis & Venkatesh	2000	PEoU, PU, Subjective Norms	TAM2	Perception based Segmentation Model
Venkatesh et al.	2003	Performance expectancy, Effort Expectancy, Social Influence, Facilitating condition	UTAUT	Perception based Segmentation Model
Venkatesh et al.	2012	UTAUT + Hedonic Motivation, Habit & Price Value	UTAUT2	Perception based Segmentation Model
Bhattacharjee	2001	Performance expectancy and confirmation leads to satisfaction	Expectation Confirmation Model (ECM)	Perception based Segmentation Model
Peppers and Rogers	2015	Loyalty, Purchasing behaviour	Behavioural	Response based Segmentation Model
Baubonienė & Gulevičiūtė	2015	Gender, Convenience, Simplicity, Product price	Demographic+ UTAUT2	Both
Belvaux and Guibert	2012	Age, Education, Religion, Extroversion	Pyscho-demographic	Response based Segmentation Model
Ul Islam et al.	2017	OCEAN with Extroversion as most significant variable	Psychographic	Response based Segmentation Model
Liébana-Cabanillas et al.	2014	Social Influence, Gender, PEoU, Attitude, Trust	Pyscho-demographic + TAM	Both
Broitman et al.,	2021	Consumption behaviour, brand loyalty, Product Value	Behavioural + UTAUT2	Both

Klarna	2020	Cohorts (Transactions, Generational & Payment Methods)	Personas	Response based Segmentation Model
Rosário & Raimundo	2021	Performance expectancy like pricing & service	TAM2	Perception based Segmentation Model
Ah Fook & McNeill	2020	Perceived Image, Emotional Self control	UTAUT3 + Neuromarketing	Both
Lee et al	2022	Gen Z, Millennials	Generational segmentation	Response based Segmentation Model
Mihova & Pavlov	2018	Loyalty & Affluence	Behavioural	Response based Segmentation Model
Lachhwani & Jain	2021	Age	Demographic	Response based Segmentation Model

2.4. E-commerce:

E-commerce is defined as “business transaction, involving the making of commitments, in a defined collaboration space, among persons using their IT systems, according to Open-edi standards” (Kunesova and Micik, 2015). This is the standard definition as adopted by the ISO/IEC 15944-7:2009.

2.4.1. E-Commerce definition & history

E-commerce has been a great success story over the last three decades. This has been the arcade of innovation with new ideas and product differentiation. As per study by Ferrera and Kessedjian (2019), the E-commerce evolution began in 1994 with launch of Netspace Navigator and online sales of Pizza by Pizza Hut. Since then, the E-commerce has scaled multiple frontiers including crossing Y2K (The great Year 2000 theory that all, \$1 Trillion in sales in 2012 to become the backbone of Industry.

Currently, the E-commerce or E-business as many terms it, is categorized in various forms like B2C (Business to Customer), D2C (Direct to customer), B2B (Business to Business), B2B2C (Business to Business to Customer), C2B (Customer to Business), C2C (Customer to Customer) and B2C2C (Business to Customer to Customer) among others based on the customer interactions between business, buyers, suppliers and end users. The early definition of E-commerce as defined by Kalakota and Whinston (1997) is sales and purchase transactions especially executed on digital media. E-Business was defined as E-commerce and the surrounding IT architecture which enables the platforms and services. A general consensus among many scholars & World organizations including UN commission on International Trade Law, GIIC, UN International Organization on Economic Co-operation and development, World Conference on E-commerce is the division of E-commerce in Narrow and broad definition. The Narrow definition includes E-transactions (online advertisement, sales, purchase) while the broad definition also includes the internal business activities like Market research, product development, finance, and customer relationship in addition to E-transactions. With the evolution of social media, connected commerce and metaverse, the boundaries between both the definition are increasingly blurred out. For our discussion on E-commerce, we shall be using the broad definition with end-to-end business management through the digital medium.

2.4.2. E-Marketing

According to Meng (2010), the E-marketing can be defined as a tool which organization use to convert potential market in reality market using modern communication technical method. Herein, Internet marketing is used throughout right from product pre-sales to after sales and servicing as well. We will use the term E-marketing as well as Internet Marketing interchangeably.

2.4.3. E-Commerce Trends

As per FIS (2022) the Global E-commerce market witnessed a growth of 14% YOY to \$5.3 tr driven by travel sector with opening of global economy. Another important insight is that of Mobile transactions in E-commerce sector overtaking Desktop transactions with 52% market share. This is a huge milestone in the device ecosystem and reflect the changing consumer preferences. The report further states that digital wallets continue to occupy the top slot with 48.5% market share followed by Credit Card at 21%. Debit Card is at 13.7%, Bank transfer at 7.4% and BNPL at 2.9%. As per the report the share of Credit card, Debit card & Bank transfer is expected to fall further by 2025 while BNPL & Digital wallet are expected further strengthen their market share. In comparison, POS transactions are at \$45 tr, posted a 13% YOY growth with strong 15% increase in APAC. There has been a decrease in Cash and Credit Card with 17.9% & 23.9% penetration respectively; a slight increase in Debit card usages at 22.7% along with Mobile wallets at 21%. POS financing constitutes 3.9% but surprising project to decrease to 3.4% by 2025. The BNPL solutions are expected to grow to 1.6% from less than 1% now. The above study suggests an enhanced role of digital wallets across both E-commerce as well as POS and optimism is high on BNPL, it can be seen that the contribution in next 5 years is going to be close to 5% through this channel growing by 3X over current penetration. The study also suggests that with increase in travel spends, there is a good possibility in incremental spends through credit card.

Another report by McKinsey (2022) suggests that 2/3rd of the profitable consumer goods companies plan to sell through food delivery platform (B2B2C) in an effort to be at the point of major customer interaction. The study also points to enhanced loyalty programs and content-first platforms to mitigate the impact of lower access to third party data (thanks to the tougher privacy laws across the world). Other pointers as identified in the study are internal talent and 360* focus on supply chain management to ensure smooth e-commerce operations. This study reflects the impact of cross platform sales and it

can be deducted that hyper-personalization, collaborations across the supply chain & presence across distribution points are going to be the key factors for E-commerce success in near future.

A contrasting report by Statista (2022) suggest that E-commerce revenue might fall by 2.5% to \$3782 Bn in 2022 burdened due to supply constraints, Russia-Ukraine war, decreasing consumer confidence and rising inflations. The study further states that Electronics as a sector has been hit the hardest, while the grocery and food chain is working fine.

2.4.4. E-Commerce Customer Segmentation

The customer segmentation towards e-commerce have been studied at length and few of the important factors understood are as follows:

The Internet marketing and customer segmentation have been studied to help marketers cater to Niche & Micro-marketing (Kotler, 2022), and as reviewed by Lin et al. (2004), “satisfy requirements of individuals (Kara & Kaynak, 1997), increase customer loyalty (Peppers and Rogers, 2015), and maximize production surpluses (Yelkur and DaCosta, 2001)”.

Another research suggests that the main reason for customers to shop online have been Convenience, Simplicity & Better price. Demographically, men are found to be more likely to shop online due to lower price while in the age group of 25-35, people are shopping for reasons like lack of time and wide range of product (Baubonienė & Gulevičiūtė, 2015).

As per the study by Belvaux and Guibert (2012), Internet users are younger, educated, sociable & less religious and they behave differently than the regular users.

As per Soman (2001), new tech payment methods have a direct impact on customer decision making, both in choice of instrument as well as the spends.

The study by Ul Islam et al. (2017), suggest Extroversion i.e., an individual's tendency to be social & interactive being the most important positively correlated factor, followed by openness to experience, neuroticism i.e., one's proneness to depression, worry & distress, & agreeableness, for personality attributes in online consumer engagements while negatively associated with conscientiousness i.e., one's propensity to be careful, organized, responsible and success oriented. As per the study, the consumer engagements were positively associated with consumer's purchase intentions. The above study highlights the impact of OCEAN on the customer purchase intentions.

As per the study by Liébana-Cabanillas et al. (2014), the external influence is a major factor in deciding the usage for online payments and hence WOM (Word of Mouth) is a major determinant factor affecting purchase decisions while Females are more likely to adopt to an online payment method due to attitude & trust; On the other side, men are likely to be enticed due to ease of use of online & mobile payments.

The above studies show the significance of demographic, Behavioural & Psychographic factors for online segmentation with younger male with higher emotional extremes are likely to be high users of E-commerce. This further shows the importance of loyalty, convenience and external influence as important factors across various research.

Implementation of Online customer Segmentation plan depends on specific Critical Success Factor (CSF) as attributed by Lin et al. (2004). The study identified six CSF for successful implementation of CS as scientific statistical analysis, a good segmentation plan, action on results, swot analysis, project resources, morale & communication. While not directly related to the Segmentation result, above study showed that only segmentation plan alone mayn't lead to correct segmentation results and other factors are equally important.

The E-commerce segmentation can be done basis the distribution reach / availability across mega apps like amazon, predictability of consumption, brand loyalty, shipping cost & value of items, along with the scope of personalization. The other key differentiator is community engagement and performance marketing for a successful recipe. (Broitman et al., 2021)

Another study for a major BNPL player Klarna (2020) in Australia suggests four personas for E-commerce users in Australia:

1. Emotional & Savvy (The Passionate approach): They constitutes 19% of the customers, of which 74% Millennial & Gen Z, 49% shop online weekly, and 32% find payment methods are time consuming. These customers are long term E-commerce users who loves to plan/ research for their dream products. Such customers feel themselves to be creative and dreamer. (Klarna, 2020)
2. Rational & Savvy (The Efficient approach): They constitutes 29% of the customers, of which 62% are Millennials and Gen Z, 35% are weekly online shoppers, and 53% worry about overspending. These customers don't spend much time online for deals but use multiple other strategies to ensure optimal purchases. These customers feel themselves to be smart and on top of things (Klarna, 2020)
3. Emotional & Less Savvy (The Ad-hoc approach): 13% of the sampled base; 71% are Millennials & Gen Z and 63% are Female, 50% are weekly buyers and 72% worry about overspending. These customers browse as a past time as well as when excited through various communications like social, ad, offers, discounts etc. As the purchases are more instinctive, many of such purchases are often not required. (Klarna, 2020)
4. Rational & Less Savvy (The Mindful approach): These are the biggest size at 39% of the sampled base. 59% of these are Millennials & Gen Z. As expected, the weekly online shopping trends is lower at 32% in this category and most of the people don't like

overspending from this category and are cautious against being taken for a ride. (Klarna, 2020)

There are studies which state that customers are using e-commerce for UX (Sagandira & Berg, 2020), better pricing, offers, great service and free return (Rosário & Raimundo, 2021). From the above four approaches it can be seen that emotional customers have highest appetite for online shopping while customers perceive themselves to be more mindful (Ah Fook & McNeill, 2020).

Table 2: Customer Segmentation

Author	Year	Author Remark	Customer segmentation & E-commerce Buying Behaviour
Kotler (2022)	2022	Niche & Micro marketing	
Kara & Kaynak, 1997	1997	Satisfy requirement of Individual	
Peppers and Rogers, 2015	2015	Increase customer Loyalty	Behaviours: E-commerce leads to increased customer loyalty
Yelkur and DaCosta, 2001	2001	Maximize product surpluses	
Baubonienė & Gulevičiūtė, 2015	2015	Convenience, Simplicity & Better price	Demographic: Men prefer online vs women due to cost; Generational: Late Millennials shop online due to Lack of time & variety of products
Belvaux and Guibert, 2012	2012	Internet users are younger, educated, sociable & less religious and they behave differently than the regular users	Demographic: Positively associated with Young, Educated, Sociable, Less religious

Ul Islam et al. (2017)	2017	Extroversion	Phychographic: (OCEAN) Positively associated with Extroversion, Openness to Experiences, Neurotorism, & Agreeableness while Negatively associated with Conscientiousness
José Liébana-Cabanillas et al. (2014),	2014	WOM as major deciding factor	Demographic: Women are more likely to use E-commerce due to Attitude & Trust (Pshycographic). Men are more likely to buy due to ease of use and mobile payment (Behavioural)
Klarna (2020)	2020		Persona: E-commerce customers are Gen Z & Millennials, Shop weekly and worry less about overspending.
Sagandira & Berg, 2020	2020	User Experience	Behavioural: Features
Rosário & Raimundo, 2021	2021	better pricing, offers, great service and free return	Behavioural: Features
Ah Fook & McNeill, 2020	2020	emotional customers have highest appetite for online shopping while customers perceive themselves to be more mindful	Neuromarketing: Emotional customers who believe themselves to be Mindful

2.4.5. Buying behaviour in E-commerce

2.4.6. Impulse Purchase

As per Parboteeah (2005) Impulse purchase is customer's propensity to purchase without any prior intention (on the go) with an exposure of an external stimuli. Impulse purchase is associate with post purchase cognitive /emotional behavioural reactions.

The integrated model as proposed by Dholakia (2000) suggest the following promoters & detractors of Impulse purchase. The promoters are '*Impulsivity of customer*' (Customer have an inherent urge to purchase to immediate gratification and also help in providing the fun of making the purchase), *Marketing Stimuli* (External stimulus for making the purchase eg., offers, discounts, occasion), and *Situational factors* (environmental: money & personal factor: mood). Detractors are *Current impediments* (Mone & Time), *Long term considerations*, and *Anticipatory consequences & emotions*.

Impulse purchase plays a significant role in E-commerce purchases as well as selection of payment mediums and vice-versa. As per study by Rachana and Sujaya (2023), close to 40% of all e-commerce purchases are due to impulse buying.

Impulse purchase especially in Individualistic society is greatly affected by reduction in friction for the payments and availability of credit. Both Credit Card and BNPL solutions works to reduce this friction. BNPL makes it much easier with their extremely flexible pay in instalment module. (Sonawane, 2021).

Another study on Gen Y & Z customers in Malaysia discuss in detail about the positive impact of payments especially digital wallets on the impulse purchase through the S-O-R (Stimulus-Organism-Response) model (Lee et al, 2022).

A detailed study on Impulse buying by Redine et al. (2022) suggests the following framework with cues from S-O-R.

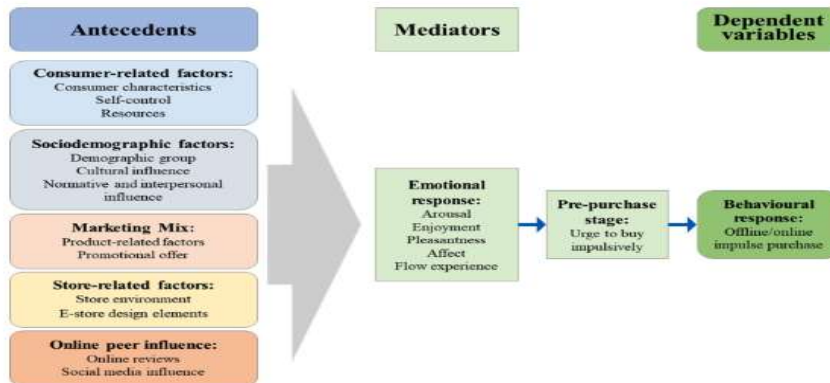


Figure 1: Impulse buying model by Redine et al. (2022)

2.4.7. Compulsive Buying Behaviour

Historically, for offline shopping, female shoppers are found to have proneness to compulsive buying behaviour. The study by C. Xu et al. (2022) suggests two specific points. Internet shopping or E-commerce leads to increase in compulsive buying behaviour which had more influence on women compared to men. At the same time, women with one or more credit card showed much higher inclination to compulsive buying behaviour compared to men.

2.4.8. Cart Abandonment

Cart abandonment is another extremely important buying behaviour in E-commerce. As per stats by Statista (2022), the cart abandonment varies between 50% for groceries to 98% for Cruise & ferries with average card abandonment rate at 71%. Cart abandonment is one of the most researched areas in E-commerce as the customer purchase cycle is almost complete but one final step.

Few of the reasons behind cart abandonment are:

2.4.9. Pain of Payment

Pain of payment as proposed by Zeller Mayer (1996), is the most significant factor in E-commerce purchases and one of the major reasons for cart dropout. It refers to *Increased payment friction* (The physical / immediate payments through Cash / Bank transfer / Debit card / Prepaid wallets) & a *Heightened sense of loss*. This results in decreased intent of purchase and higher cart abandonment. Pain of payment is also inversely proportional to the perceived value of the purchase; higher the PV, lower would be the pain of payment. Pain of payment also increases with convoluted and complex checkout process and requirement for account / card details fill up. Any last-minute additions in terms of tax, charges or other such cost also leads to incremental pain of payment.

2.4.10. Decision Paralysis

Many a times customers start doubting their purchase decision during the journey which manifest to a complete decision paralysis at cart checkout stage. This leads to customer postponing (or even cancelling) their purchase. Most common reasons behind decision paralysis are *Choice Paralysis* (Availability of supplementary options as details by Bocken Holt et al., 2017), *Post purchase anticipatory consequences* (probability of negative emotions and financial loss post purchase), *Financial dilemma*, and *Negative cues*.

2.4.11. Need Elasticity

A term coined by the author which suggest the probability of the purchase is highly dependent on the degree of requirement for the product. If the product need is elastic i.e., customers can postpone the purchase without any significant loss, the chances of cart abandonment increase significantly. Vice-versa, if there is an immediate and urgent requirement, the chances of cart abandonment reduce significantly. Few of the factors as detailed by the author under this attribute are:

- How important is the purchase?
- When is the product needed?

- Customer's personal attitude towards purchase (Impulsive / Compulsive behaviour)
- Self-control & Societal pressure (Emotional Quotient)

2.4.12. Checkout Inhibitors / Promoters

The effort expectancy to complete the checkout, trust in payment mode & failure rate, past experience with the checkout, review ratings, and return policy, are few of the inhibitors / promoters for the checkout process.

2.4.13. Consumer Emotional Intelligence:

Another very interesting theory on decision making and an offshoot of larger EI discussion, CEI was first discussed by Mayer & Salovey (1997) and conceptualized by Kidwell (2008) in detail. This discusses the customer's ability to understand and channel emotions

2.5. Customer Purchase Decision

2.5.1. Customer purchase decision lifecycle

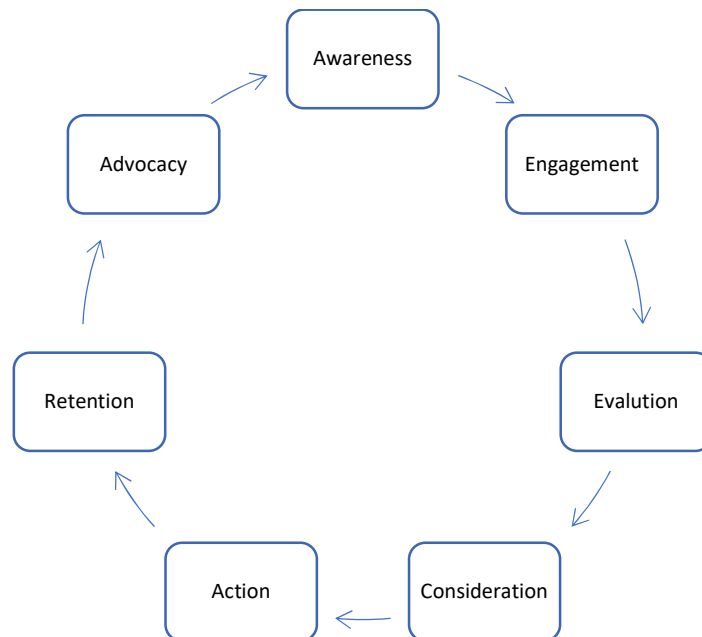


Figure 2:Customer Purchase Decision Lifecycle

2.5.1.1. Awareness:

This is the stage where customers become aware about the product / services being offered. For existing services and products, this can be a reinforcement of the product existence and benefits.

2.5.1.2. Engagement:

This stage is where the customers get involved with the product / services and want to learn more about them.

2.5.1.3. Evaluation:

At this stage, the customers are evaluating all the options available to them and want to compare products.

2.5.1.4. Consideration:

At this stage, the customer has shortlisted the product / service as one of the choices and is looking to consider the list for a final closure.

2.5.1.5. Action:

This is the most important stage in the customer lifecycle as the actual closure happens at this stage for the product.

2.5.1.6. Retention:

At this post purchase stage, customer needs to be supported with the usage understanding and creation of a loyalty program for the customer for repeat purchases and high satisfaction.

2.5.1.7. Advocacy:

At this stage, the customer is delighted with the services / product and has become a brand ambassador for the product /service, bringing in addition customers

2.5.2. Type of Customer purchases

2.5.2.1. Based on customer Needs

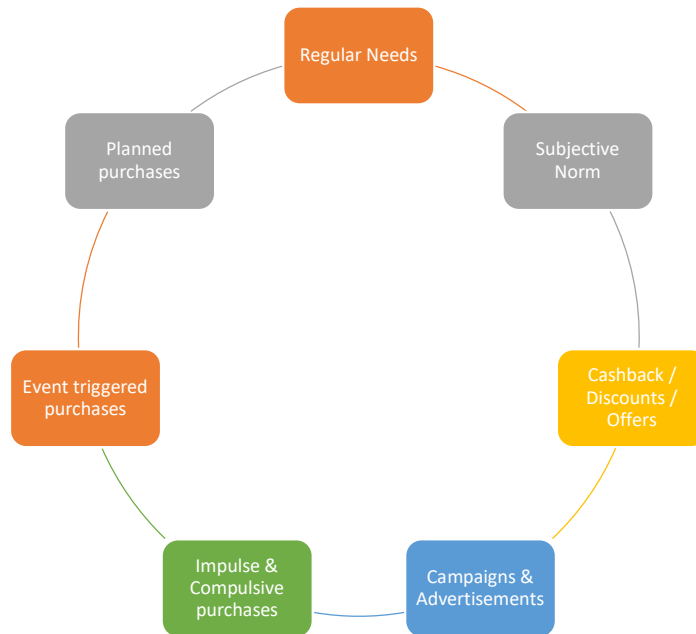


Figure 3:Type of Customer Purchases

2.5.2.1.1. Regular Needs:

These purchases are small value, high frequency purchases wherein the customers use high choice of payment mode, slightly modulated by offers. These are daily need items like groceries, bill payments, small ticket subscriptions among others.

2.5.2.1.2. Subjective Norms / Social Influence:

These purchases are small to medium value purchases wherein the buyer’s perception of how others want him to behave and what others are actually using, decides the purchases. These are generally electronic goods, garments, & accessories among others. These purchases are more aligned to impulse buy and are higher with reduced pain of payment. The cashless and post-paid payment modes are most apt for such purchase decisions.

2.5.2.1.3. Cashbacks, Offers & Discounts:

An additional offer or discount act as a huge trigger for impulsive purchases as it increases the perceived value for the product thus decreasing the pain of payment. While the average value per item differs during these purchases, the overall cart value increases significantly. This also helps in reduction of cart abandonment. Most of the times, these benefits are associated with a specific payment type (Mostly credit cards / Wallets).

2.5.2.1.4. Advertisement & Campaigns

Advertisement & Campaigns act as a great catalyst in bringing out the latent wants & desires of a person. It decreases personal resistance to subjective norms, increases perceived value and pushes for impulse purchases. A slightly differentiated form is WOM (Word of mouth), a strong interpersonal communication medium which also helps in enhancing the subjective norm & perceived usefulness, while also increasing the perceived trust for the product, company & payment mode.

2.5.2.1.5. Impulse Buying & Compulsive Purchases

While we have discussed these types of purchases in detail earlier, they are worth mentioning here as many times, the purchases are done just for the sake of purchase without any underline requirement or trigger. These purchases are generally small value. The chances of cart abandonment are very high in these types of purchases.

2.5.2.1.6. Event triggered Purchases

This type of purchase can be divided into two categories; namely: 1) For any specific purpose of event, 2) Due to any specific event & outcome. These purchases are very specific and time bound. The payment mode will generally vary with customer.

2.5.2.2. Based on type of product purchase

Table 3: Customer Purchase Decision

Geography	Frequency	Value	Involvement
<ul style="list-style-type: none"> • Domestic • Foreign • Urban • Rural 	<ul style="list-style-type: none"> • One time • Recurrent • Intermittent 	<ul style="list-style-type: none"> • High Value • Medium Value • Low Value 	<ul style="list-style-type: none"> • High • Low • Medium

2.6. Attributes Of Tech (AOT) Theory: 6A’ of Digital Purchase Decision

While the Diffusion of Innovation theory and Facilitating conditions in various new age models (UTAUT 1/2/3, TAM 1/2/3) discuss about the perceived qualities of a product / tech with self and society for the tech adoption rate, the full stack relationship and attributes of tech and its relationship with both buyer and supplier is not well detailed. To create deeper insights and additional understanding of this behaviour patter, the author proposes the conceptual model as 6A’ of customer for the Purchase decision digitally (including choice of payment mode)

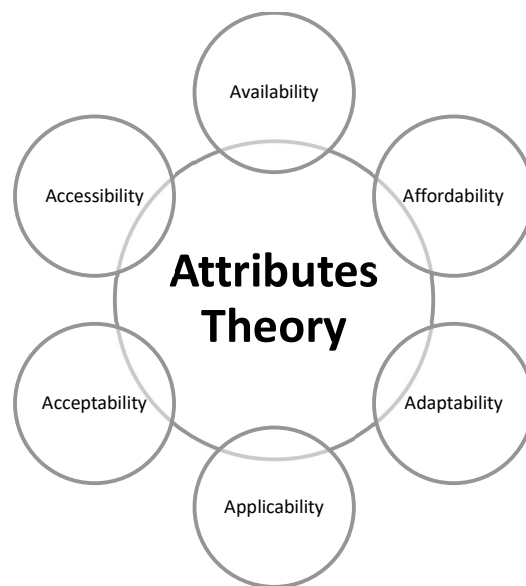


Figure 4:Attribute of Tech II (Source: Author)

2.6.1. Availability:

Availability of the service is the basic requirement for the customer and suppliers to be able to use & provide the services which is further moderated by Affordability, Adaptability, Affordability, Acceptability, Accessibility. While the plausible useability of the model is across all customer decision models, the author has created this model for the customer mode of payment choice. Widespread Availability is the factor driving this. Availability itself is moderated by availability of payment choice and availability of facilitating conditions (Venkatesh, 2012;2016)

2.6.2. Affordability:

Affordability refers to customer's income and access to funds including credit for the purchase. In terms of E-commerce and digital payment method choice, this factor takes in account, the customer's income, creditworthiness, ability to pay. Affordability act as one the main drivers in choice of prepaid vs post-paid as well as own cash vs credit-based payment choices. From the seller's perspective, this is the associated cost, charges, infrastructure requirement and payment probability.

2.6.3. Adaptability:

Adaptability refers to customer's acceptance to innovation and new technology. This involves the customer's technology adoption rate, receptiveness to innovation and intention to use new product and methods. Adaptability also means same user experience across mediums and payment methods. UI /CX plays a big role in ensuring adaptability of the customer and help bridge the habit hurdles. Adaptability of a tech product is dependent of complexity

2.6.4. Applicability:

Need for the product as well as customer's involvement in the process is measured through this parameter. The purchase decision will differ with the change in requirement urgency and applicability. As per the author based on the proposed theory, this factor is positively associated with

Perceived usefulness. The factor also reflects the importance of situational circumstances, along with special needs of the customers and other stakeholders.

2.6.5. Acceptability:

Acceptability of services is measured by this factor as despite all other factors conforming to the requirement, if the services are not accepted by either the buyer or the seller, the purchase won't take place. In terms of choice of payment method, the acceptability of digital payment (specific / overall) by the merchant is a significant factor in using Cash, COD, or any specific payment method while, the acceptability of payment method by the customer is moderated by higher education, age and confidence in electronic payment (Pinter et al, 2021). The acceptance of payment method by the merchant and customers are also moderated by subjective norm, PE, Hedonic motivation, Habits, EE, and price value as discussed later in the research. Acceptability of payment method is also affected by pecuniary cost associated with the electronic payment to the merchant (Welte, 2016). These costs are generally MDR, set up fee and settlement interest which is generally offset by customer convenience, incremental spends by customer and income independency of the customer leading to increased revenue by the merchant.

Research by Yasin & Ahmed (2022) in Somalia suggest that an absence of acceptability of mobile payment by major E-commerce players leads to restriction in choice of payment method.

2.6.6. Accessibility:

Access to tech, product, communication, and medium leads to significant impact on customer decision making. As per Yasin & Ahmed (2022), online payment choice and trust affect the accessibility of E-commerce in Somalia. The study also reflects the important of geo-political factors in choice of payment method. According to another study by Osang (2017) in Nigeria, continued accessibility of medium is one of the major factors in improvement of usages of medium and services.

2.7. Fintech Landscape

Fintech is a short for Fintech Technology as described by Kagan (2019), which has gained significant traction in last decade. The search for the word Fintech on Google has significantly increased in last five years as shown by Google trends. This reflects the increasing popularity of the term.

While the history of Fintech goes back to 1866 with setup of transatlantic cables (Agrawal, 2021a), the first use of Fintech word can be traced to Citibank’s project named “Financial Services Technology Consortium” in a 1993 report (Hochstein, 2017; Arner et al 2015). Financial technology (Fintech) is used to describe new tech that seeks to improve and automate the delivery and use of financial services & vice-versa with innovations in financial literacy, banking, crypto and investments (Gomber et al, 2018). At its core, fintech is utilized to help companies, business owners and consumers better manage their financial operations, processes, and lives by utilizing specialized software and algorithms that are used on computers and, increasingly, smartphones (I. Lee and Shin, 2018).

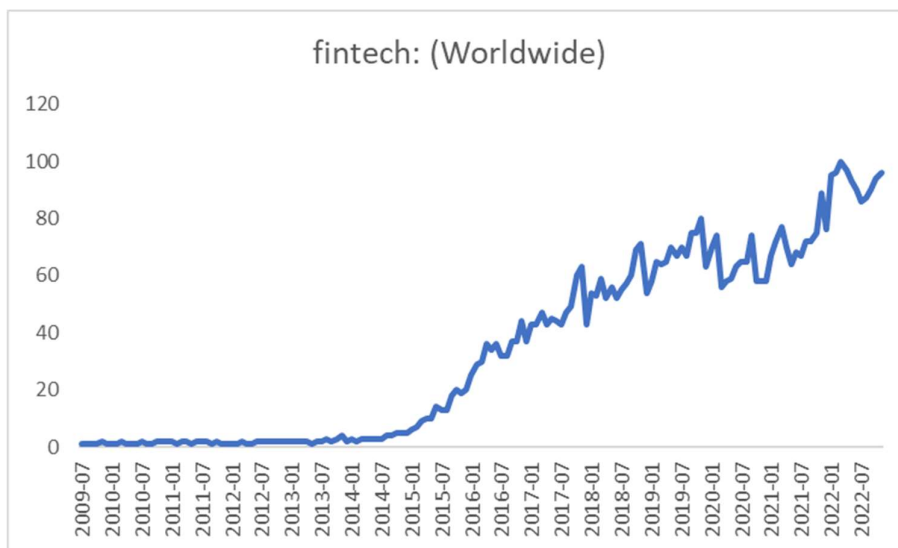


Figure 5: Google Trends Fintech Worldwide

Additionally, researchers create a definition to ensure that Traditional banks with tech enhancements are not treated as Fintech lenders stating that the player should be from outside the traditional banking industry (Cornelli et al. 2020 and Ziegler et al. 2021: Fintech lending).

2.8. Fintech Categories

The fintech comprises of following categories in general: Wallets, Digital Payment Gateways, Insurtech, Wealthtech, Regtech, Cryptocurrencies, Digital Lending, Alternate Finance, crowdfunding, Neobank, BNPL among others (Zavolokina et al., 2016; I. Lee and Shin, 2018).

2.8.1. Wallets

A digital wallet is generally an online repository which securely stores customers details of various payment methods like UPI, Cards & Banks and act as an easy payment method completing purchases without the need to remember card details. The wallets can also have the capability to have digital cash for making online and offline payments. Few of the bigger examples of wallets are PAYTM, Paypal, Apple Pay, Phone Pe etc (I. Lee & Shin, 2018).

2.8.2. Digital Payment Gateways

Digital PG are one of first innovations in fintech landscape. It allows for Fintech companies to integrate multiple payment modes like cards, Crypto, UPI, Banks at the POS. These companies can act as direct acquires or Payment service providers (PSP) to allow for integration of multiple acquirers. Advance options like switching let merchants switch between multiple PSPs depending on the transactional requirement. Additionally, these fintech are implementing cutting edge technologies like DLT, tokenization, multi-level encryption for customer data security (S. Agarwal & Zhang, 2020).

2.8.3. Insurtech

Insurtech is a very popular fintech model wherein modern insurance sales & distribution, underwriting, claims and policies are driven by AI/ML based algorithms and many traditional companies are also shifting many of their functions to these platforms. Few of the famous Insurtech companies are PolicyBazaar, Coverfox, Acko among others (Pritchett, 2019).

2.8.4. Wealthtech

Wealthtech has gained significant momentum recently thanks to implementation of Roboadvisory by many of the large wealth management companies as well as new gen Fintech companies (Abraham et al, 2019). The report further states that a lot of investment decisions including hedging, Swaps, Currency, derivatives, assets are being driven through algorithm based advisory leading to specific insights which are otherwise ignored or impossible to identify by regular financial advisors.

2.8.5. Regtech

Innovation in regulatory control, services and advisories are driven by Fintech innovations. Lot of regulatory compliance requirement in current complex matrix of geographies, demographics and modes becomes extremely difficult to manage. These are managed through Data driven, AI/ML, Algorithm based requirements for AML, cyber security, supervisory tech, internal risk management and compliance requirements (Arner et al, 2017).

2.8.6. Neobank

Neobanks are digital fintech powerhouse which provide extremely agile, fast and consistent banking solutions including offering online accounts, budgeting, finance automation & saving tools. An offshoot of neobank is Payment bank which are predominantly digital bank with far better regulatory framework. In Indian context, these payment banks can accept limited deposits and have restrictions on assets, loans & card side. These payment banks are guided by the regulator and license driven. Many of the Indian NBFCs & Fintech have applied for a payment bank as the initiation point for larger approvals. Few of the major companies are Airtel, India post, Paytm, Aditya Birla, Fino, Vodafone among others (Asma et al, 2022).

2.9. Fintech Consumer behaviour trends from across the world:

- As per new research by The Finfluence Report (2022) of LinkedIn, 52% of the customers are buying from brands aligned to their personal values. The fintech have to start thinking in these lines wherein they go beyond the regular product sell to connect with the customer at an empathetic & personalized level across values, ethics, environment and communication. The study further identifies the impact of community and metaverse on the customer behaviour as well as a shift towards flexibility at work in post covid era.

One very interesting insight is that now average American is using Fintech Apps (88%) more than video streaming subscription (78%) and social media (72%). The study further highlights the importance of financial literacy, inclusivity, empathy, B2B2C & internal marketing as other factors driving consumer interest in 2022 (N. Agarwal, 2022).

2.10. Digital Lending

Finance have been evolving continuously to help ease the consumer convenience and provide additional ways for transactions to sail through. One of the major developments is the concept of

lending which led to significant spurt in purchases and transactions. As per the article History of Fintech by Agrawal (2021a), the ATMs (Automatic Telling Machine) were the first true digital footprint for any financial transactions, a vast improvement over drive in car kiosk as experimented by Missouri banks during 1930s. The Diners card and then the Credit Card overall during the 1950s changed the way payments are made. The rise of Internet & mobiles during the 2000s ensured a far more connected economy with need for more evolved and digital financial tools. The E-commerce boom also meant that aspirational & impulse purchase needs increased significantly (Y. Lee et al., 2022). This led to creation of innovative digital lending products to cater to ever growing demand from consumers. FinTech lending can be defined based on the type of the customer-lender interaction or on the technology that is used to onboard & track borrowers (Berg et al, 2022).

- Customer-lender interaction: Fintech lending labeling would be applicable if the customer-lender interaction is purely app-based or purely online
- Onboarding & Tracking: Based on the technology used to onboard & track customers, or on use of AI /ML to write rules for these, the research on fintech customer segmentation is generally limited to commercial understanding of local effects and similar is the case for Islamic Fintech.

2.11. Digital Lending Categories

Fintech lending can be also categorized based on following Peer to Peer Lending, Lending Marketplace, Supply chain finance, SME Lending, Line of Credit, Invoice Finance (Thangaraj, 2019):

2.11.1. Peer 2 Peer Lending (P2P):

P2P lending is an innovative lending method wherein in its simplest form, individual lender is connecting directly with prospective borrower without any intermediary; read bank or NBFC. In

evolved forms, there are NBFCs who are working as the right platform to connect and match these prospective lenders (Either individual, SMEs or corporates) with prospective borrower based on derived algorithms with the help of AI/ML. As per the Bachmann et al. (2011), Online P2P lending started with Zopa in Europe (UK) in 2005, followed by Prosper.com in US with more open access to scientific community in 2007. P2P lending is affected by demographic and social factors in addition to their eligibility.

2.11.2. Loan Marketplace:

These are digital platforms wherein the prospective borrowers compare and research loans from various banks and NBFCs and based on their match, continue to avail the loans or any other digital lending from product from these institutions.

2.11.3. Supply chain finance

In this popular high value model, the NBFCs are lending money to distributors, wholesalers, marketplace operators to cater to their sourcing and credit needs.

2.11.4. SME Lending

SME funding is another rising sector in the Digital lending with Project financing, product launches, marketing among other expenses. These are generally small ticket B2B lending enabled through a digital medium. A very similar funding model adopted by niche players like Moneytap wherein they give small ticket Business loans as line of credit. In this model, Businesses can borrow, repay and again avail the credit up to a predefined credit line with tenure between 2-36 months and interest.

2.11.5. Line of Credit

This is very similar to a credit card wherein a credit line is extended to customers who can withdraw and pay back within the provided credit line. The line will automatically get replenished every time it is paid back.

2.11.6. Invoice finance

Short-term credit provided by lenders for small and medium enterprises based on unpaid invoices of these prospective borrowers. This is a hugely popular lending tool for B2B financing.

2.11.7. Online & Mobile lending platform

In this model, the end-to-end lending is provided from online & mobile platforms digitally.

Another innovative digital lending tool is embedded finance wherein the digital lending & payment options are embedded with the e-commerce, offering retailers an enhanced approach to make customer convert purchases anywhere in the site. While practically invisible to eyes, these solutions help customer spend more time and money on the page, help in preventing attrition to competition and early closure of deals.

2.12. Comparison of Fintech lending vs Banks

A comparison of parameters based on multiple research (pwc, 2015; Bao & Huang, 2021; Balyuk et al, 2020; RBI, 2021; ABA & Accenture, 2021, Loutskina, 2018)

Table 3: Fintech Lending vs Banks (Compiled by Author)

Parameters	Fintech Lending	Banks
Processing speed	Very Fast	Medium to Slow

Credit Scoring requirement	Nil to Low	Medium to High
Ease of use	High	Medium
Regulatory requirements	Low	High
Digital connect	High	Medium to Low
User Experience	High	Low
Distribution Strength	Medium	High
Cost to customer	Low	Medium to High
Personalization	Low to Medium	Medium to High

2.13. Customer segmentation for Digital Lending:

As per Mihova & Pavlov (2018), the customer segmentation for commercial banking is aligned to loyalty and affluence of the customers. As per Lachhwani & Jain (2021), the Fintech and digital lending are now being used across products and demographics. Convenience has been identified as the most important factor followed by Safety, Income and adaptability. The research also identifies age as a major factor affecting fintech lending. (Lachhwani & Jain, 2021). Fintech lending customers are generally segmented based on demographic, social and eligibility factors.

2.14. Regulatory impact for Digital Lending and future implications:

With increased losses of existing fintech lenders and a higher propensity of debt exposure for the larger market much beyond the repayment capacity, the regulators have started bringing in policies, guidelines and compliance notes to bring in the requisite order to the current chaos. Various policy articles by RBI (2021), Sandstone Technology (2022) highlights the growing impact of regulatory requirement on Digital lending. Tritto et al (2020) highlights the impact of regulatory requirements on digital lending in Indonesia.

2.15. BNPL (Buy Now, Pay Later)

With the enhancements in the Cards & Payments industry, the role of EMI (Equated Monthly Installments) especially Zero cost EMI has been significant to allow customers to buy expensive items and then pay it in installments over a period of time (Berg et al., 2021). BNPL is considered as any payment which is made in four installments or less (*What Is a Buy Now, Pay Later (BNPL) Loan?* 2021), but there are various other versions with larger number of installments as well. As per RBI (2021), BNPL is defined as POS (Point of Sale) financial product wherein borrower is allowed to purchase product with a deferred payment and pay in predetermined instalments.

2.15.1. BNPL McKinsey Models:

The most accepted BNPL model is McKinsey and Company (2021) model, which identifies the following major models in addition to Physical Point of Sale Financing.

2.15.1.1. Integrated Shopping Apps:

This is one of the most interesting platform models of BNPL as many of the large conglomerates have started offering end to end shopping experience right from prepurchase to post-purchase in an effort to enhance consumer experience through engagement across the purchase cycle. Few examples of such super apps are Tmall, Ant, Tata Neu among others. Companies like Klarna, Afterpay are using this model wherein the customer begins his journey on these apps, subsequently moving to shopping apps for purchases. The transactions in such apps are generally from high return categories and lot of impulse buying thanks to the Zero cost EMIs to cashless shopping experience offered by BNPL.

2.15.1.2. Card-linked instalment offerings:

In this type of BNPL solution, the companies are creating innovative card based BNPL product or deep co-branded &/or merchant specific card linked products with flexible EMI options. This type

of BNPL solution has gained significant pace in Asian & LatAm markets (PayU, 2022). The BNPL credit card in Indian markets like Slice, LazyCard, Unipay and deep cobranded cards like Onecard, Bajaj Fin RBL cobranded card are offering such plans which gives customers additional benefits and flexibility in payments. There are pay in 4 cards in European markets which offer convenience to customers with minimum documentation and maximum outreach (CB Insights, 2022).

2.15.1.3. Off-Card financing solutions

Off Card financing solutions are the most popular BNPL solutions. In this model, merchants either through seamless tie-ups, in-house or integrated solutions provide instant credit to buyers with additional offerings like discounts, zero APR, low-cost EMI among others (Mastercard, 2021). These purchases range varies significantly from small ticket size to high value. Generally, buyers in this segment have access to traditional credit cards but opt for BNPL solutions for lower APR & flexibility in repayments (Mastercard, 2021). Famous India BNPL providers through this model are Flipkart pay later, Lazypay, Travel & Educational portals offering integrated EMI solutions among others.

2.15.1.4. Virtual rent-to-own model

This is a very innovative lending model wherein the buyer lease or rent a product with an intent to purchase it by making the complete payment with time. This model helps create a market which was largely under-served till now. As per a report by Lux (2022) for Harvard, it has been highlighted that Virtual rent-to-own model customers general score is less than other financing solutions ($70\% < 600$).

2.15.1.5. Vertical focused larger ticket players

For big ticket financing like an international holiday, a major medical emergency, an expensive purchase, higher education with payment flexibility, this model is being used. The model helps a

customer meet their important & necessary requirements by making access to larger credit easy and approachable.

2.15.2. SME sales financing

We have already discussed this previously as a lending tool. For short term loans with limit flexibility & lower APR, SME sales financing is gaining popularity in B2B segment.

As per M2P Fintech (2021), BNPL advantages for Consumers, merchant & Fintech companies are as follows. The consumer get access to instant credit leading to fulfillment of impulse purchase desires, access to credit for segments with lower credit scores, zero to lower rate of interest. For merchants, it means driving higher sales, AOV, customer retention and decrease in cart abandonment.

The Fintech companies get access to newer segments, customer portfolio, merchant acquisition and loyal base. This makes it an overall win-win story.

2.16. BNPL impact on Credit Cards & Personal Loans

There are very few studies on consumer behaviour and factors affecting BNPL. As per study by Ah Fook and McNeill (2020), there is a strong correlation between impulse purchase and availability of BNPL. The study further corroborates the assumption that BNPL is leading to higher conversions both in offline and online mode and also heavily impacted by Sales conversion tools. These studies positively explain the impact of BNPL on incremental spends by the consumer and increase in inclusiveness by making more non-consumers to buy. There is a very strong notion among the researchers that BNPL will make the credit card obsolete in near future (Alcazar & Bradford, 2021). As per the current study, 30% of the Australian consumers are using BNPL. The most significant highlight of the study was that in absence of BNPL offerings, the customers are likely to switch to Debit Card with majority of the customers determining that credit card & wallets are important factors

for online purchases. The study further analyses that geographical reach of Banks & access to credit is another important factor for Fintech BNPL segment to grow due to increased inclusiveness for the customers. While the study suggests that BNPL will be able to replace credit card in future, there is a good possibility of both targeting different segments of users with some interference and both will continue to co-exist thus increasing the overall reach of credit to customers.

Another study by ASIC (2020) suggests that 48% of the customers didn't find any change in their credit card pattern while a small percentage suggested that it has increased post BNPL usage. 42% of the customers suggested that their usages have come down post BNPL usage. One more highlight of the study was slightly incremental trust on BNPL solutions with 90% of the surveyed population trusting the product. The study also suggests that BNPL customers have grown in terms of financial literacy and are managing the spends in far optimal and matured way. (The Strawhecker group, 2022)

Another article by Jude (2022) suggested that the customers using BNPL solutions are more likely to spend more and checkout with fuller cart compared to Credit card. An important pointer discussed in article is about a decreased pain of paying with BNPL thanks to a credit line without time limits leading to higher purchase propensity for the customers. This is a significant finding from the retailer view and this may lead to higher preference for BNPL solutions compared to other payment methods.

2.17. BNPL Landscape in India

As per the Ken Research (2022), the Indian BNPL market has grown at a CAGR (Cumulative Annual Growth Rate) of ~321% in FY19-21. E-Commerce & Food aggregators provide ~39% of total GMV (Gross Merchandise Value) Online BNPL demand is much higher than offline POS transactions with South zone contributing most to the BNPL. The report further states that demographically, age group 26-35 years account for ~40% market share due to recent employment, lack of credit access and

frequent purchases. Additionally, the factors affecting acceptance of BNPL are ease of on-boarding, app stability, low penalty & good customer service among others.

The report segments the Indian BNPL market in four:

1. App based BNPL players like Lazypay (biggest player with 39% GMV share), Simpl, Zest Money, Cashe
2. E-commerce / Travel aggregators like Amazon pay later, Flipkart pay later & Ola post paid
3. Card based BNPL: Postpe, Slice, Dhani, UNI pay etc
4. M-wallet BNPL: Paytm Postpaid, Zip Pay Later, Freecharge Pay Later

A report by HDFC Securities (2022), suggest that BNPL is already close to 1/3rd of credit card users. The expected CAGR (Cumulative Annual Growth Rate) till FY26 is 74% for BNPL which makes it one of the fastest growing products in the market. As per the report, the BNPL growth contributors are access to credit for NTC (New to Credit) customers, seamless integration with the payout, immediate approval & lower fees charges. Interestingly, the report suggest that credit card has better value proposition vis-a-vis BNPL and the later will act as the feeder for credit cards by providing access to newer segments. This is in contravention to most other reports which suggest that BNPL will replace credit card in future except for the ASIC (2020) study.

According to PYMNTS (2022), BNPL is used by older customers with higher purchasing power to manage their finances and use it to do larger purchases; both necessities as well as discretionary. The study further finds veterinary and dental treatments as most uses BNPL solutions. This study also identifies luxury purchases as another segment with high interest from Bridge Millennials and Millennials.

As per A. &A. amount.com (2021), BNPL has been discussed for financial institution in following models.

1. Marketplace partnership
2. Rent a platform partnership.
3. Card platform partnership

2.18. BNPL Customer segmentation & Factors affecting BNPL adoption

Impact of Gen Z & Millennial on Fintech & Online Shopping: Fintech has been the flavour of the day with lot of technology-based innovation which with every passing day looking at acquiring new segments and expanding into newer area of operations.

As per the study by Daqar et al (2020), one of the most crucial factors for fintech adoption and customer segmentation has been the availability and usage of technology especially smartphones. The rise of smartphones has led to easy access to fintech products especially payment. This has also led to higher usage & acceptance of fintech among the Gen Z segment as the technology adoption rate is very high here. The challenge for Gen Z is lower access to financial systems due to credit ineligibility (A. M. Abu Daqar et al., 2020) and thus while this segment act as a great influencer for the family purchases offline & online, 81% of them do in-store purchases (Mckinsey, 2021). This is in fact breathing life in Brick & Mortar format reeling under the onslaught of E-commerce. Millennial are better exposed to the financial systems and have comparatively higher eligibility from traditional bank vis-a-vis Gen Z. Both Millennial & Gen Z use online payments & E-wallets (84%) and have used fintech at least once in last one year. Additionally, there has been a change buying pattern of these segments due to social distancing and covid related environment with increased adoption of online shopping. Gen Z are also using BOPIS (Buy online & pick in-store) as one of the most preferred shopping media. While Millennial want amenities, Gen Z want a secure life but are more driven to financial gains over work life balance (D Brown, 2020)

Regardless of buying power, the research from Vice, Adobe & Insider suggest that Gen Z are more pragmatic spenders vis-a-vis millennial despite on being more digitally savvy and are less influenced by advertisements. Millennial are expected to be more of impulse buyers compared to Gen Z due to their attraction to adverts and amenities. For BNPL, both have attraction with separate benefits and segmented differentiation. Gen Z with lesser access to formal Credit (Read Bank, loans & Card) gets attracted to Alternative scoring model with higher approval based BNPL solutions while millennial go for BNPL in case of high value purchases like smartphones, EV with easier payment options across in-store and online stores.

Another study by Payments Journal (2021) suggests BNPL to be more popular than short term loans, being more popular in age group 18-24, middle income and having limited access to credit. The study further suggests equal customer segmentation between online and offline module with offline modules tilted towards interest bearing loans and online transactions tilting toward zero cost EMI. The study further notes that BNPL are likely to be the last-minute decision and mostly facilitated by Merchants directly vis-a-vis 3rd party for other short term loan solutions.

The above studies on BNPL customer segmentation suggest “external influence” for Millennial and “access to credit” for Gen Z as important pointers.

Another study suggest that US Men (63%) vs US Women (52%) are more likely to use and have used BNPL in past one year. The study further suggests that BNPL is 3X more likely to be used by 18-34 years vs 55+ year customers (Backman, 2022). The above study clearly identifies the demographics as key factor for BNPL segmentation. The above study is limited to US customers and more detailed understanding is required to correlate the same for other geographies especially India.

Another study by PYMNTS (2020), Clothing is the most important segment of usage at 63.5% interest. Clarity of fees and interest rate (41.7%) as most important factor for BNPL interest over Credit Card

and debit card. This is followed by ability to monitor spending at 39.1% vis-à-vis 24% for Debit card & 21% for Credit Card.

Another report by Bain (2021) on BNPL in UK market suggest BNPL to be more famous and used by young, digital native customers compared to Credit Card. The study further suggests no difference in household income, gender on BNPL usages. There is another good insight from the report is that BNPL is being used by both category of people: With credit exposure and without credit exposure. This is in contravention to other studies which highlighted access to credit as important driver for BNPL. The report further states that BNPL is used by young consumers for low value repeat purchases while older customers are choosing it for higher value purchases with major purchase line is spreading across clothing, shoes & electronics. The report identifies these four factors for consumer interest in BNPL namely, 'Cost saving compared to Credit Card especially for missed payments', 'Help in managing the finances'; 'increases the affordability of products', and 'ease & convenience'.

Another report suggests that 54% of the surveyed online shoppers of a large E-commerce site in UK prefer BNPL over Credit Cards with Convenience, flexibility and Low interest rate coming as top 3 factors for this preference (C+R Research, 2022).

Another study suggests the adoption of BNPL by Gen X (54%) and Baby boomers (63%) to be very high in India vs rest of the world. The study further suggests 'not wanting to take debt' as a major barrier for BNPL while 'Give it a try' as major driver for the same (RFI, 2022). More study is required to understand their potential and segments.

Research by PYMNTS and PAYPAL (2022) suggest that customers use BNPL for large purchases while prefer to use Store cards inside a store thanks to higher reward ratio.

A study on 1000 verified BNPL users in US identifies three very demarcated personas for such usage: The Convenience Seeker (Millennials, Middle income customers who likes easy checkout and treat

BNPL as any other payment medium and use it for small ticket everyday items, travel & riskier purchases); The Debt Avoiders (Older, High-income customers, who treat BNPL as payment financing. These customers are more likely to use BNPL for >\$2000 & travel related spends); The Novelty Lovers (Gen Z & late Millennials, this cohort is more likely to be made of Male customers who are well educated and have a hesitancy towards BNPL purchases for high value & riskier items. These customers treat BNPL similar to credit card and more likely to pay BNPL debts through Credit Card) (Cardify.ai, 2021). One important point to note from this study is that despite of being debt avoiders and novelty users with BNPL hesitancy, customers are still using the payment method which indicates an intrinsic and latent market for all category users for the product.

Research by Maurizka et al. (2021) suggests perceived usefulness, perceived ease of use, lifestyle benefits, social influence, attitude towards debt, perceived risk and trust as major drivers affecting adoption of BNPL by customers.

Research by Pratika et al. (2021) in Indonesia suggest that BNPL usage is directly affected by the credit eligibility of the customer. The research also suggests that BNPL leads to increase in impulsive buying tendency in consumers.

2.19. BNPL Niche Markets:

BNPL is currently at 3% of total payments market and is expected to go to 5% as discussed earlier. There are already multiple signs for weakness in the market with cases like ZIP creating nervousness in the market. Regulators across the world are also pushing aggressively to bring control and guidelines for the BNPL sector. While this is a good move in long term, it has added to the existing shakiness.

There are people discussing about saturation in this segment in addition to serious questions on long term sustainability & profitability of the sector. One of the ways to identify the BNPL solutions for Niche markets and further evolve the product to meet the customer needs.

This review takes cognizance of existing corporate reports and articles in this field due to extreme paucity of published academic articles.

One of the suggestions for creating this niche market is verticalization of the sector beyond retail into Healthcare, Travel & Home Improvement (The Strawhecker group, 2022). Another online article by Finovate suggest Education, Travel, Health and Housing as sectors with existing companies providing BNPL solutions (Julie Muhn (@julieschicktanzt), 2022).

In a podcast interview, Stuart Thornton (Co-founder, hoolah) discussed at length about the significance and scope of B2B BNPL solutions citing lack of focus by FI as well as opportunity for providing technology upgrade in this field (Kowan, 2022). Another research seconds the significance of B2B BNPL as an important niche with extension of technology for fraud detection, analytics to organizing their workflow & payments. (Smirnov, 2022)

2.20. Checkout Crowding & E-commerce Impact

With BNPL becoming omnipresent, the number of BNPL options for E-commerce site is going to explode and it is pertinent to identify the average number of BNPL players put on a portal to optimally provide right customer experience.

2.21. Credit Card

2.21.1. Overview, Stakeholders & Models

Credit Card is a special variant of unsecured line with aided advantage of convenience, safety and acceptability thanks to interoperability between relevant stakeholders. Credit Card began in operations with Diner card offering a line of credit for payment of restaurant bills.

Credit Card generally consist of six important stakeholders as per Chakravorti (2003)

1. Consumer or Card holder

2. Card Issuer
3. Merchant
4. Acquiring entity
5. Card Network
6. Payment gateway

The credit card can be defined by various sourcing models depending on distribution, type of offering & value proposition (Murowaniecki, 2015). Few of them are

1. Inside Sales: Telesales has been one of the most ubiquitous models of credit card since its inception wherein the customers were enticed and asked to apply over a call. The advantage of this model is that of location independence, ability to reach out to larger base and comparatively connect with a desired customer pool. Another very prominent way of inside sales is cross-selling on companies' other products like Branch A/c, Loans, Servicing etc. Few modern iterations of this model are performance marketing, SMS campaigns, social media marketing, Google ad campaigns among others. The new age inside sales models also means lower control on acquiring base while increasing the spread of customer base (Roongta & Priya, 2017).
2. Open Market Sourcing: This is another popular model for credit card sourcing with customers being approached outside the company & partner ecosystem. This can be as simple as selling the card through pure cold calling, placing a kiosk near point of interactions, non tieup corporate sourcing, sourcing near malls, petrol pumps, Airport among others (Mehta & Agarwal, 2021).
3. Partnership or Co-brand Sourcing: Partnership sourcing is an extremely powerful combination of loyalty, rewards, outreach to new segments among others. In this model, Credit card company ties-up with partners to offer co-branded cards with additional loyalty benefits within the partner ecosystem. This is true win-win with a strong loyalty program for the partners, access to newer segments of customer as well as segmented card offering to niche customer base. The co-branded

cards are also found to have increased perceived value & customer attitude towards co-branded card store / bank (Tingchi Liu et al., 2012).

4. DSA & Fintech partner: This is one of the most effective way to inorganically the acquisition for any credit card company. These fintech partners will have access to unique customer base and their outreach will ensure increased trust for the customers. An interesting study by McCoy et al., (2012), suggest that customers onboarded through the DSA (Direct Sales Agent) are more satisfied, loyal & profitable.
5. Direct sourcing: This is the model wherein customer themselves connect with you to apply without any distribution system. It can be end to end digital or in other cases, customer approach the bank, customer service, or any other direct source to apply. Another direct sourcing model is referral wherein existing customers refer their friends & family for the cards, and mostly are covered with lucrative reward program.

Credit Card can also be defined basis the card category (Chase, n.d.):

1. Regular cards: These are primary card type of any card issuer wherein they give rewards, discounts and benefits across segments as per card features. Few examples are like Gold, Silver, platinum card to name a few.
2. Co-branded Card: These cards are issued in partnership with any other company wherein the card holder enjoys additional benefit across the partner ecosystem and this act as a great loyalty program. According to the research by Zhao et al. (2021), the cobranded card leads to high customer loyalty, increased product & card awareness, and customer retention.
3. Special purpose card: These cards are created with specific usage in mind and while there is no partner, the card offers exclusive benefits in the particular targeted segment. A travel card is one of the best examples for this segment wherein customers get access to benefits on various travel transactions. Another example of this type is shopping card aimed at boosting retail purchases while providing higher rewards on specific categories.

4. Secured Card: Generally, most of the card companies are averse to providing credit card to customers with limited or derogatory Credit history. In contrast, a secured card is issued against a lien and by nature, risk free for the issuer. This enables issuers to open various untouched segments for this card.
5. Corporate card: These cards are issued with corporate liabilities and risk is borne by the employers.

2.21.2. Credit Card Customer Segmentation

As per study by CGI (2014) on a large financial consumer base especially for credit cards & Banking services, Loyalty & Rewards program was found to be one of the most important factors with 81% of the customers expecting them to be valued for their total spends and rewarded for loyalty. This was closely followed by omni-channel presence of the product & services. The other important parameters were personalized service, Investment advisory & analysis. The study also noted that poor service, lower cost elsewhere and security issues were most important parameters for switching the banking & card services.

In line with this, another study suggested that rewards & incentive can influence behaviour as well as change the brand perception with 56% of the respondents conceding that personalized incentives make them consider the financial brand. (Virtual incentives, 2017)

Another study on Loyalty program found the dissatisfaction in loyalty marketers in the financial industry with the performance of the loyalty program. Only in cases with multi-channel integrated programs aided with high engagement mechanism, a better traction in the program was reported. (Deluxe Corporation, 2015).

Another study in Africa by Umuhoza et al. (2020) suggest following customer segmentation for credit card using K-means clustering namely Regular users, fashion lovers, prosperous, and limited spenders

with differentiated marketing strategy for each customer segment. The study further identifies Loyalty programs, rewards, Ease of use, Personalization & Priority service, discounting as few of the parameters which are of significance to users in these categories. These finding though based in Africa can be a significant testing ground for use cases elsewhere in the world.

From the above review, it can be discussed that credit card customer segmentation follows the E-commerce segmentation with loyalty, convenience and personalization. A more detailed study to understand the impact of external influence on credit card usage is required. On the other hand, BNPL has been sparsely researched for customer attitude and behaviour academically and current studies points to external influence as one of the major factors for taking it.

Further, interesting research by Turton et al. (2021) identify debt attitude and impulsivity as few of the important traits & attitude responsible for intake of credit. This study has been done in an international context and a regional study is required to study the impact of various psychological factors.

Another study by Fiorio et al., (2014) suggests that with evolving trends, the age old Behavioural (Transactor, Revolver, Subprime) & Demographic (Income, Age, Geography) aren't helping in incremental growth as per the business expectations. This is primarily due to increased competition within similar offerings in all segments mainly differentiated through Rewards, Low-Rate & Subprime. To overcome this, the report suggests five new Need-based segmentations based on customer requirements:

1. Prosperous & Content: With high income & very high share of wallet for cards, and mainly being transactors, these customers want high rewards, convenience & ease of use. An EMI option to convert occasion high purchases will work well with such cards. Another requirement of these customers is personalized service & personal attention.

2. Deal Chasers: Customers of this segment are high revolvers, loves co-branded card and are having good positive outlook towards economy & self. They love shopping online and are always looking to close a transaction at the lowest cost. Despite being high revolvers, these customers have sufficiently decent income. These customers love occasional deep discounting and offers while budgeting between distinct purchase categories.
3. Financially stressed: These customers are heavy revolvers and carry 4X more debt than average. These customers generally have financially gloomy outlook of themselves and the world. These customers expect transparency, information & generally have self-imposed spending limit. These customers will also have defined pay-off horizon for major purchases.
4. Recovering credit user: These users have lower revolved rate, low affinity to rewards & offers and seldom use credit card for non-essential purchases. These customers are looking for personal connect, spend monitoring tools across categories, and occasional waivers on fees from the issuers.
5. Self-aware avoiders: These users also have debt aversion and hence would like to use debit card & cash over credit card. These customers look for transparency & simplicity in fees, payments & terms just like financially stressed and providing the confidence of mishap avoidance and repayment plan & calculators can help in making these customer better credit users.

The above study provides a very different take on the customer segmentation with need of the customers being the paramount importance. Post Covid scenario needs to be understood for these segments based on altered customer needs and outlook. Additionally, the above study was done when BNPL was not a dominant force, with many of the needs directly being satisfied through the BNPL solutions, there is a possibility of cannibalization of the market share by such solutions and different segmentation might be required.

The study by Klee (2008) based on the research on transactional data suggest that while Age is positively related to use of Cash, the credit card usage with age follows a non-linear trend with late millennials (35-44) are least likely to use Credit card. The study further highlights that Education levels are positively related to usage of credit cards. In addition to this married couples are also more likely to use Credit Card compared to single customers.

Another study by Alam et al (2022) on Credit Card customers in Malaysia finds that the most differentiating factor that influence customer credit card purchase decisions are Cashback and Interest rate charges. The study also points out that there is no impact of Annual fees, late payment charges as well as monthly annual income are not significant features for the card.

As per the report by Bandi et al. (2019), customers using digital payments, purchase expensive items, have higher basket size and order value while having a lower rate of return of goods purchased. The report further corroborates with the pain of payment theory of Prelec and Loewenstein (1998) by decoupling the payment from consumption by usage of digital payment methods.

2.21.3. Credit Card Landscape in India:

Indian Credit card industry is comparatively at a nascent stage compared to other developed markets. In a population of close to ~1.4B with close to ~500M smart phone users and 150M online shoppers in FY21 which is expected to grow to 800M by FY26 (HDFC Securities, 2022), India has a meagre credit card penetration of 1.4% accounting for 8.3% of GDP compared to 4.3% penetration with 33.2% for US (HDFC Securities, 2022). The current credit card count is ~70M and growing at a CAGR of 15%. The number of transactions per credit card is 31.2 and has ~35 players offering retail credit card with HDFC Bank leading the chart with ~16.5M customers followed by standalone card player SBI

Card at 13.3M (Kothari, 2022). With expected growth in E-commerce and access to credit by customers, Indian Credit card industry is expected to leap forge significantly.

Research by Khare et al. (2012) identifies Convenience, external influence & status symbol, and financial security during emergencies as major factors driving credit card usages across the world. Some of the other factors influencing credit card usage are income, gender, and rewards. The study finds Use, Convenience, Age, Gender, Sense of belonging, and Sense of fulfillment as important factors affecting India consumer credit card usages. As the study was done pre demonetization and before the advent of digital revolution, a new understanding is required especially for factors like sense of belonging, age & gender.

2.22. Personal Loan

Person loan is one of the oldest asset products with variation going as back as 4000 BC. In simplest term this is giving money to an individual based on trust. The more commercial way is by analyzing prospective loan taker's ability to repay over a period of time. Personal loans have come a long way with various alternative forms like short term personal loan, Digital lending, P2P lending, Small Ticket personal loan, large value person loan among others.

The Loans are provided by Banking & Non-Banking lenders (Eg. P2P, NBFCs, Credit Card Cross-sell, Mortgage companies). Typically, loans from non-banking lenders are given for riskier segment with higher interest rate (196 basis points higher compared to Banking lenders). (Loutskina, 2018)

Another study suggests a dramatic shift in consumer behaviour as well as the offering channels during & post pandemic in India. There has been a huge surge in demand for personal loans with close to 100% for Rural & Semi urban segment and ~150% for urban locations. Also, with Mobile first approach & quick distribution, NBFCs and especially Digital NBFC have garnered majority of market

share at close to ~83%. The report also suggests that 85% of the loans by Fintech are of less than 50K value while for banks it is around 1L. (Parashar & Nanaiah, 2022)

2.22.1. Customer segmentation for Personal Loan:

As per the report by CRIF - Highmark (2022), young, first-time buyers with age less than 25 years are driving personal loan growth in India with 2.3x growth in value and 3.4x in volume with ~70% of the loans in less than 10k ticket size which is dominated by NBFC accounting for ~93% of the market share. 19% of the personal loans are provided to NTC customers. 54% of the loans in ticket size less than 10k and 50.6% in 10-25K are provided to age group 26-35 years. For 50k+ personal loans maximum share belongs to 35+ years. The report gives a great insight about the factors affecting Personal loan which includes Age, Access to Credit & Lender type.

Another study by Augustino using the survival analysis on Indonesian customers suggested Age, Marital status, no of dependent, living status, education, region, job type, length of work, salary, interest rate, Credit Tenure, & Credit Limit as major impacting variables for Top up personal loans. One significant point was that Gender doesn't play a role in the customer propensity to take top up personal loan. The study also identified that various customers have their own personalized mix of requirements out of Tenure, Interest rate & Credit Limit and appropriate product should be provided to increase uptake. (Augustino et al., 2017)

2.22.2. Customer segmentation for Personal Loan in India:

A study suggests that the customer segmentation for personal loan is done based on employment type of customer i.e., Self-Employed or Salaried. The study further identifies that Gender & Marital status doesn't have a significant role in case of loan approvals for the customer. (Tiwari & Somani, 2021)

2.23. Digital Payments & Wallet:

Digital payment is increasing replacing cash across all segments gradually with POS cash transactions cash is expected to drop to below 8% by 2025 and Cash on Delivery with medium as Cash being already at less than 1% for the E-commerce industry (FIS, 2022).

Digital Payments have been growing both in retail as well as B2B segment (Especially in Real time payment) thanks to Covid driven tech adaption, change in consumer preferences, convenience, real time access to credit and favourable regulatory and government policies and support. (FIS, 2022)

A report of RBA (2020) suggested a dramatic shift from cash to digital payments between 2010 to 2020 with mobile based payments moving up significantly over the period. The increase is significant across all product categories, age, income range and geographical diversification. Two significant pointers for the report are

- Customers use cash because they want to use their own money and keep it for emergency use
- Impact of benefits of card proposition has come down over the researched period

The current research is heavily focused on Gen Z and Millennials while the Baby Boomers are still most dominant force with high net worth. Boomers still manages 50% of the total wealth with Gen Z accounting only for 4%. Boomers and Millennials have shown higher inclination towards Digital payments and Boomers have started increasing their usage of digital payments with aim for higher rewards, visibility and transparency (Schauer, 2021). Previous research by Balgobin et al. (2016) suggests that use of Non-bank payment method significantly boosts online purchase intention.

There are various digital payment instruments available for consumers:

1. Credit Cards
2. Debit Cards & Bank transfer

3. Prepaid cards & other PPI (w/o credit line)
4. Digital Wallets
5. POS Financing
6. Real time payment (UPI, RTGS)
7. BNPL

We have already discussed about Credit Card & BNPL earlier and shall be discussing other digital payment modes here.

As discussed above in the review, Digital wallets are the major drivers for Indian payments. There are various factors affecting the usage of wallets including influence of service features, external communications, perceived benefits, perceived usefulness, consumer attitudes, perceived risk, convenience, and security (Koranti & Putri, 2019; Mahawadha, 2019)

2.23.1. Digital Wallets: Attributing Factors & Customer Segmentation

As per the study of Digital wallet customers in Indonesia, the report suggests the major factors driving Digital wallet usage are usefulness, ease of use, and innovativeness. The study also note that digital wallet usage is driven by factors like personal experience, perceived security, subjective norms, and job relevance. (Fanuel & Fajar, 2021)

Another study on digital payment customers in Vietnam suggest performance expectancy (Usefulness), effort expectancy (Ease of use), Social Factors (lifestyle) and facilitation to be positively related to usage of Digital wallet while perceived risk is negatively associated with usage. (Hoang et al., 2021)

A similar study in Saudi Arabia also identifies Perceived Usefulness, perceived ease of use, lifestyle compatibility, and facilitation condition as factors affecting digital wallets (Alswaigh & Aloud, 2021)

Studies by T. Lee (2005), Lin & Wang (2006), Luo et al (2010), and Nguyen et al (2016) have identified Trust as the most important factor for E-wallet & Mobile commerce adoption.

Another study in Delhi India to examine the impact of attitude along with TAM model suggest that while attitude plays a significant role in all five TAM variables, it is significantly affected by provision of financial incentives to start using digital wallets. (Kumar & Gupta, 2021)

Another study also signifies the meditating impact of Age & Gender in lifestyle compatibility of the users while adopting Digital wallets. (Yang et al., 2021)

The major factors for E-Wallets in India as per the study of Bagale (2023) are Perceived Ease of use, Awareness, Compatibility, Perceived Security, Perceived Usefulness and Trialability. The research also suggest that Attitude & Innovativeness are insignificant factors in choosing Digital wallet in India.

2.24. Islamic Banking & Payments:

With increased requirements of rich Islamic countries, and to reach out to larger consumer base as well as to tap into the wealth of these clients, Islamic banking & financial system was created around 1960s. Few of the popular Islamic financial Instruments (IFI) are Sukuk (debt financing – Bonds), Murabaha (Cost + Fixed Fee), Mudarabah (Profit loss sharing), Musharakah (Joint ownership), Ijarah, Istisnah, Salaam, and Takaful (insurance). There are various other instruments as well which are used in combination or as a standalone product to fill the banking requirements.

These products have created a huge market for themselves with current size of the IFI is measured at \$2200B which is expect to grow to \$4500b by 2027 at a CAGR of 12.67%. (MarketWatch, 2022). Another report indicates that IFI has crossed 25% of total asset size in GCC countries thus becoming systematically important in these countries. The report also highlights those strong investments in Halal, Sukuk, Takaful & Islamic banking (\$1.9T) is leading the growth. Islamic banking contributes

close to 69% of total IFI with GCC accounting for 44% followed by MENA (26%) & Asian countries (24%). (Market Data Forecast, 2022)

2.24.1. Islamic Finance:

Islamic Finance is based on the principle of Sharia which considers the following activities prohibited as well documented by Suyono (2017), Khaki and Sangmi (2011), Siddiqi (2006).

According to Siddiqi (2006), the requirement for Islamic finance has been raised in 1950s to ensure a RIBA free trade and bring fairness. Since then, from a humble beginning it has come a long way and is now a multi-billion-dollar segment. In general, the below mentioned factors are the main driver of Islamic Banking across the world.

1. Being involved in anything that is considered Haraam (Illicit I.e Gambling, liquor, betting, non-halal foods, speculations to name a few)
2. Riba (Riba or interest is prohibited in Sharia and hence it creates the difference between the conventional and Islamic banking as Bankers need to identify a different modus operandi to generate revenues and profits)
3. Maisir (Speculation): Speculation & Gambling is strictly banned as per the Sharia laws
4. Gharar (Uncertainty/Risk): Participation in financial activities with high uncertainty and risk is not allowed as per the prevailing guidelines. This along with Maisir effectively rules out Future, derivatives and other similar products.

This makes access to Banking & Credit through traditional medium also non-existent as almost all Asset/Liability products carries interest component. To negate this, Islamic banking professionals have created very innovative products like Murabahah, Mudarabah, Musharakah, Bai Muajjal, Sukuk among others.

The following details have been taken from the above source as well as through personal expertise in the field.

1. **Mudarabah:** In this, one party (Rabb-ul-Mal) provides 100% of the capital and another party (Mudarib) provides the labour, energy and time. The first party is mostly a sleeping partner and the profit is shared based on pre-agreed distribution. Loss is generally only shared by the party providing the capital (Siddiqi, 2006).
2. **Musharakah:** This type of product is based on the principle of joint ownership, wherein two or more of the partners can contribute in terms of both capital and labour with all partners sharing profit & loss in pre-agreed ratios. This type of investment tool is generally used for infrastructure projects, line of credit etc. A special derivation of this is Musharakah-al-Mutanaqisa (Diminishing partnership) wherein the share of one or few of the parties keep diminishing over time in return of incremental payments by other parties. This is popular for home loan financing involving Ijarah (Leasing of bank asset share by the customer) & Bay' (gradual sale of banks asset share to the customer). (Siddiqi, 2006; Khaki and Sangmi, 2011)
3. **Murabahah:** This type of asset-based financing is done through an arrangement wherein both the parties agree on a cost+ price. Herein Bank buys the product on behalf of customer and sell it to them at a predefined cost + markup. In case the payment by the customer is on deferred basis, in installment or payment in whole at a later date, this is called Bai'al-muajjal or BBA. This is the most common Islamic product (Khaki and Sangmi 2011).
4. **Bai-al-Inah:** This is a reverse asset financing arrangement for provision of loans wherein one party buys an asset from the other at spot price and sale it back to the same party at a markup who then pays for it in installments. This is slightly controversial as per the Sharia laws (Suyono, 2017).
5. **Bai Salam:** Bai Salam or a Salam contract is agreement to receive goods & services in future by making an advance payment. In this type of contract, all terms including, place, price, delivery

mode, date of delivery, quantity, quality among others are fixed in beginning and can't be modified. Many FI use parallel Salam contracts to get into contracts with both seller and buyer acting as intermediary (Khaki and Sangmi 2011).

6. Istisna: Like Bai Salam, Istisna is also a forward contract agreement for buying a product which wouldn't have been manufactured, processed, or constructed if not for the contract. Herein, the terms are comparatively flexible with payments made as per the schedule rather the full advance as well as delivery dates being modifiable. The payments can also be made in installments compared to onetime payment in Salam contracts (Khaki and Sangmi 2011).
7. Tawarruq: A tawarruq is a complex contract wherein one party gets into an agreement to raise cash by buying an item from FI who would have bought it from suppliers at spot price on Bai Muajjal basis (repayment on deferred basis generally in installment on markup price) and reselling the same item to the FI at a discounted price. The FI will sell the product to another buyer at a spot price + fees. Tawarruq is one of the most important products in Islamic fintech as many Islamic credit cards & BNPL products are based on these guidelines (Siddiqi, 2006).
8. Takaful: As exposures with risk /uncertainty is banned in Islamic banking, it effectively takes away the normal insurance system. To circumvent this, Gramin bank in Bangladesh has devised Takaful which is now accepted across the world as the Islamic Insurance. In this system based on mutuality, the insurance risk is shared by all the insurance holder through a common created pool which is managed by a manager from the Agency (read Insurance company). The funds of this pool are invested in shariah compliant schemes and profit is shared by all the insurance holder (Suyono, 2017).

Additionally, for a product to be Shariah compliant, the product has to undergo Shariah guided auditing & accounting practices (Khaki and Sangmi, 2011).

1. Zakat (Obligatory charity), Sadaqah (Voluntary charity) & Waqf (endowments) are seen as great tools for alleviating poverty & bringing inclusiveness across the world.

2. Ijarah (Leasing or renting contract) is another very important IB product for leasing of goods, properties or at times services. This can be used in conjunction with partial payments towards purchase to convert it into a lease and sale agreement wherein at the end of the lease, the property belongs to the lessee.

Sukuk is another important financial instrument wherein the bonds are issued with part ownership for the investors to avoid the Islamic rule of ban on investments without any underlying assets (Khaki and Sangmi 2011).

2.24.2. Islamic Fintech:

With the increased adoption of Fintech, Islamic finance can adopt many of the technological enhancements to enhance its outreach and benefits to customers. According to Alshater et al. (2022), there has been increased research on Islamic fintech between 2017-2022 and suggests that it is time to cointegrate Fintech in Islamic Finance.

There has been significant research in the areas of Crowdfunding (Baber, 2019; Biancone et al, 2019; Hendratmi et al, 2020), Cryptocurrency (Elasrag, 2019; Abojeib & Habib, 2019; Ajouz et al, 2022) and Sukuk among others.

As per the Consultancy-me.com (2022), the Islamic Fintech is expected to grow at 21% CAGR compared to 15% for traditional fintech in OIC countries till 2025 representing a 125Billion market of over 1 billion customers.

Another report by World Bank Group (2020) on financial inclusion terms Islamic banking as one of the drivers for financial inclusiveness. With 41% of OIC customers not having account ownership vis-a-vis 92% for high income countries and religion being a significant reason for not having an account, Islamic finance can help increase financial inclusiveness in these countries. Also, the study notes that

with Zakat contributing between \$200B to \$1Tr, it can help significantly in reducing the poverty through obligatory donations. The study further notes that P2P finance as the key Fintech technology adoption within the Islamic fintech landscape with 65+ companies in this segment.

With over 200 million potential customers not having access to accounts & Financial systems and 11% of the world Muslim population as per the above report, India can present a big opportunity for alternative systems like Islamic Fintechs to help with financial inclusiveness. India also can be the next big thing in Islamic fintech due to it's potential attraction to non-muslim customers and a more research is required to understand the possibility of interest by any customer segments within non-muslim for Islamic fintech products especially BNPL. As Islamic BNPL will generally means nil to low interest rates, nil charges, access to larger international funds among others.

2.24.3. Customer Segmentation for IFI

According to a report on IFI in Indonesia, there is no demarcated demographic segmentation based on age, gender, education, marital status, occupation, and income. The report also identifies that the four psychographic segments: Religious conviction, economically rational, religious conviction and economically rational, and ethically observant are also having minimal customer choice effect due to business requirements. Though the report also pointed out that customers were be willing to switch for all categories if similar services and benefits are extended for Islamic banking as well compared to conventional banks. There is another insight that many doesn't find current IFI to be fully Shariah compliant and hence see it futile to switch to IFI. (Gayatri et al., 2021). The above study is crucial from the point of view that with parity of benefits and service levels, a larger market size is willing to switch to Islamic finance.

2.24.4. Islamic Finance as BNPL Niche

BNPL & Islamic finance can be clubbed together to create huge B2C, B2B or B2B2C products which offer best of both world with RIBA free, ethical service to both Muslims & Non-Muslims customer base. Currently, there have been successful launches of BNPL + IFI product to offer Shariah compliant BNPL platforms. There have been few such new gen companies offering B2B as well as B2C solutions in GCC & SE Asian countries.

From the theoretical understanding of both BNPL & Islamic Banking as depicted above, BNPL in its original form isn't Shariah compliant due to it being Interest bearing, allowing non-shariah compliant purchases and not managing other audits. Few of the solutions provided are converting the transactions into three without charging any interest, fees or fines. As per Capco (2021) report, there are many large players in Islamic BNPL market which are working on either complete waiver of Interest or fees or a combination of Mubarahah & Ujrah (Fees against service rendered)

2.25. Payment Methods and its impact on decision making

Multichannel consumerism is defined as a customer using multiple channels to use a service. The customer can buy online, offline or D2C as discussed earlier. There is a gap in understanding the customer segmentation based on the payment methods adopted by the customers and researchers are looking forward to understand the payment context on buying behaviour (Runnemark et al., 2015). Ferrao & Ansari (2015) has suggested that the different payment method affect the buying behaviour of the customer. As per their research as well as that of Cheng & Chen (2016), consumers tend to buy more when using payment method as Credit & Debit Card. Bisht et al (2015) has deduced through their research that different payment methods has different attributes due to varying payment instrument.

A significant study by Hasniawati et al. (2020) in Indonesia suggest that Socio-economic factors leads to substitution pattern both between cash and non-cash methods, and within the non-cash methods as well.

A detailed study by Fujiki (2020) in Japan suggests that while Cash & Automatic Withdrawal (Autodebits) have been a payment method of choice for Japanese people in the past, the popularity of Credit card is fast catching up, in line with the Japanese government directional push for non-cash economy. The study also suggest that low income and older age people prefer cash compared to card.

As per the research by Greenacre and Akbar (2019), introduction of cashless mode of payment result in change in price perception in low-income group while not increasing the overall spends.

The study by Klee (2008) suggest that the choice of payment methods is based on the opportunity cost, handling cost & transaction size. The study also suggest that payment method is also chosen based on asset allocation also.

As per Chatterjee & Rose (2012), the payment methods can be influenced in online purchases if multiple payment options are present.

The research by Cohen and Rysman (2013), suggest that Income is one of the most important factors for choice of payment method. Additionally, the study also found that almost 100% of the respondents were using multiple payment instruments.

Another study by Vinitha & Vasantha (2020), suggest Perceived Ease of Use, Trust, Perceived Usefulness, Quality & Satisfaction along with acceptability to change in lifestyle as some of the attributes affecting choice of payment instrument.

Demographics has a significant impact on the choice of payment instrument. As per the white paper by O'Brien (2022) in USA, the age and income are major dominant factor with people with higher income choosing credit card, lowest income groups cash and middle-class choosing debit card as their payment method. The study also highlights that there is a significant drop in Gen Z cash usages between 2019-2021. It may be noted that these changes and higher non cash usage may be partially attributed to pandemic impact.

Another study by Merhi et al. (2021) suggest moderating impact of gender on adoption & choice of digital payment method for Lebanese people. The study also highlights geographical significance as the same study identified no moderating effect of gender for British people. Study by Liébana-Cabanillas et al. (2014) further corroborate the impact of gender on payment choice with men intent to use a payment system is higher than women based on the perceived usefulness; while the perceived trust impacts attitude to use a particular payment system more for women than men.

A report by Petrock (2021) for Insider Intelligence details the adoption of digital payment methods by Gen Z customers. Gen Z customers have started using less cash, credit & debit card while moving to digital wallet as major choice of payment instrument, thanks to reinvention of products like paypal,

Apple pay among others. Another significant point of interest is the suggested usage of mobile app / watch as the choice of payment over webapp / website by Gen Z customers.

Another study by Xu and Riedl (2011) highlights the usages of Neuromarketing consumer behaviour tool (Eye tracking) in defining the choice of payment methods and identified perceived trust worthiness and perceived product uncertainty as two independent variables.

Table 4: BNPL vs CC vs PL

Parameters	BNPL	Credit Card	Personal Loan
Tenure	Short to Medium term	Short term	Long term
Eligibility	Access to customers with limited Credit bureau	Requires good credit history	Requires good credit history
Documentation	Minimum documentation	Basic documentation	Detailed documentation
Amount	Medium to large value	Small to Medium	Large value
Interest Rate	Low	High	Medium
Offering Institutions	Fintech / NBFC	Banks / NBFC	Banks / NBFC
Distribution Availability	Limited but increasing	Omni channel	Omni channel
Approval time	Instant	Short to Medium	Medium
Type of Lending	Unsecured	Secured / Unsecured	Unsecured

The research by Berg et al. (2021) on fintech lending has identifies many important pointers on the market landscape namely BNPL is the fastest growing Fintech lending product and within the BNPL, Marketplace lending has peaked after an initial growth burst. The study also identifies key advantages of Fintech lending over traditional bank as elasticity in response to dynamic requirement changes, faster processing time and improved user experience. The other advantages are use of non-traditional methods for credit assessment but contrary to general view, this paper suggest the benefits due to this is limited vis-a-vis banks. The paper also suggests limited outreach to excluded & under-served borrowers despite availability of non-traditional data with these fintech lenders.

The above research seeds requirement for new exploration opportunity to understand the impact of Fintech lending & especially BNPL in a regional context.

2.26. Impact of COD on E-commerce & factors affecting it

The COD (Cash on Delivery) is one of the dominant payment systems across the world. In many geographies like South Africa (10%), Thailand (10%), Vietnam (18%), Philippines (15%), Indonesia (11%), and Middle East (10%) among others, where this still commands more than 10% of the market share for E-commerce. (FIS Global [FIS], 2023). Indian E-commerce COD is at 5% while POS Cash is at 27% as per the above report.

The study by Halaweh (2017) suggest Security, Privacy & Trust as impacting factors for COD in E-commerce. This is important to note as an increase in COD payments will lead to decrease in Digital payments and thus it can be suggested that these factors also have an impact on the Digital payments in E-commerce platform.

A paper by Maisyura et al. (2022) suggest that COD is the payment of choice for more than 60% of the consumers in Indonesia and leads to 30% increase in sales for major online e-commerce companies offering this payment method.

The study by Pencarelli et al. (2018) in Italy suggest factors like Online reputation of the seller (Negatively associated with COD), domestic companies vs foreign sellers (domestic companies has higher COD), choice of payment methods (positively associated with COD) & negatively associated with online support by seller.

The study by Polasik and Fiszeder (2010) in Poland interestingly suggest that the research on payment methods in E-commerce didn't identify Security as one of the important differentiating factors for choice of payment methods among Banks, Cards & COD. Another insight by the study is the lack of access to cards leading to change in payment choice method for many customers.

The research by Alotaibi & Faleel (2021) in Saudi Arabia suggest that while COD (39%) is the preferred method of payment for Online shopping followed by Cards (31%), the card is being used by 50% of the respondents to avoid overspending.

The study by Rimenda et al (2022) in Indonesia suggest that COD is chosen by habit of customer lifestyle & personal attributes like avoidance of overspending, concern for privacy, along with young, educated customers with lesser access to credit and promotions for the method. A very curious insight from this research has been that choice of payment is not heavily dependent on perception of technology & perceived ease of use.

The study by Anjum & chai (2020) in Pakistan suggest that COD in E-commerce is positively affected by perceived control on purchase (Inspection of product, easy return), perceived security threat from scammers & Ease of use. The study suggested that perceived trust & perceived satisfaction are not important factor for Pakistani customers when choosing COD.

Research by Wu et al. (2020) in China found a direct effect of order size & type of device on the payment method with an increase in probability of COD with increase in order size and choice of

method as Mobile device. The research also suggest that frequent usage of mobile device leads to diminished co-relation between the device type and the COD.

2.27. Impact of Digital Wallet on E-commerce and factors affecting it:

As per various research done on the impact of digital wallet on customer behaviour intention to use E-commerce, there has been a differential & moderating impact of digital wallet on various usage factors.

As per the research by Handayani (2020), Digital wallets have a direct impact of the online impulse buying behaviour (OIBB) and significantly, also act as the positive moderating factor against the quality of website. This result creates the need to understand the impact of various payment factors on e-commerce and their effect on changing the way, E-commerce is done.

Another research by Y. Y. Lee et al. (2022), suggest perceived enjoyment, visual appeal and user experience using E-wallet has a direct moderating impact on Online Impulse purchase while perceived interactivity of wallet overall cancels its impact on online impulse purchase.

The research by Chresentia and Suharto (2020) suggest an extended UTAUT2 model to explain the significance of E-wallet on consumer purchase intention in E-commerce in Indonesia. The important parameter is addition of trust as one of the most significant factors. They also found price-value to have a high significance. The author extends this model for Indian markets with help of additional parameters.

There is another study by Hashim et al (2022), which enhanced the list of independent variable and dependent variables along with moderating factors based on Perceived risk, Perceived Trust to further

explain the variances for intent to use the E-wallet in Malaysian market. One interesting aspect is addition of Islamic Financial Literacy as one of the independent variable in this study.

2.28. Fintech landscape in India:

As per the E&Y & Chiratae Ventures (2022), Fintech (excl. payments) in India is expected to be at \$1Tn in AUM at a CAGR of 29.8% & \$200 Bn in revenue with 3x increase in funding. 50% of this is expected to be coming through digital lending at \$515Bn. The report highlights the positive impact of regulatory and government policies for the explosive growth in the Indian Fintech market. Indian markets have been traditionally focused on payments with payments expected to grow from \$16.4Tn in flow currently to \$106.2Tn by 2030. This is majorly driven by UPI (Unified Payment Interface) which is a unique proposition offering real time payments for P2P (Peer to Peer), B2B & P2M (Retail Payment to Merchant) transactions. The current challenges for the India payment industry are: preference for cash in Tier III cities and self-employed markets, limited opportunities for revenue, and lack of trust due to minimal physical presence (HDFC Securities, 2021). The exiting future trends in Indian payment industry includes SOFTPOS, mPOS, CBDC (Central Bank Digital Currency) & Wearables largely through NFC (Near Field Communication) linked payments. Another exciting fintech enhancer is the rise of Super Apps in India with many established fintech and retail players moving into space. This helps immensely in vertical as well as lateral expansion thanks to the embedded payments and finance overall. BNPL has significantly gained momentum during & post pandemic, still the future growth trajectory will be much dependent on the policy framework by the central nodal authorities. RBI has recently brought in regulations to curtail modularity for FLDG (First Loan Default Guarantee) and co-lending which used to be most favoured modus operandi for these players (RBI, 2022). As per the report, the market is ripe for creation of marketplace model for these players which helps avoid counterparty & operational risk for these small fintech companies significantly. Zero cost EMI model adopted by players similar to international fintech BNPL players have gained huge traction in domestic market.

Another important business highlighted in the report is Neobanks offerings with focus on specific micro segments with better, user friendly features and product propositions. This includes segments generally bypassed by traditional banks like Teenagers, special Millennials & Gen Z, Rural & SME/MSMEs.

The above report signifies the importance of India in Fintech universe suggestive aggressive growth path for the payments & other fintech line of business. One of the major pointers from the report is the significant impact of regulator and support of government in overall development of this Industry.

Another extremely important highlight of the report has been the financial inclusion driven in India through the fintech revolution. The three important factors driving it are mainly: UPI; small bite sized products in both lending & insurance especially for Tier3+ cities; vernacular apps, e-kyc & vkyc based documentation, and alternate scoring models for new to credit customers.

Another study identifies Digital payments as the most preferred payment method in India and despite high regulatory entry barriers, global biggies have been investing significantly in the Indian market. (JP Morgan, 2021)

As per the report *2020_10_Working_Paper_Inclusive_Digital_Banking (2020)*, 83% of the male and 77% of the female population owns an account and overall ownership went up from 53% to 80% between 2014 to 2016. One important finding was the use of cash by 49.3% of the users. The study finds that 91% of the customers between age group of 18-40, along with salaried as 43% & self-employed at 28% while students, homemaker, & retired individuals making up for the rest. The study further identifies value propositions such as simple, affordable & accessible product, and fast & customer centric on-boarding.

As per the EandY (2021) report, the fintech in India is being driven by three factors; Macro factors like Government support, public infrastructure, demographic opportunities & funding environment,

Technology driven factors like technology advancements, increased collaboration between banks & fintech, strong technology talent pool, and customer driven factors like tech savvy customer base, & value sensitivity of customer driving innovation. The above study also discussed about the challenges faced by the sector including data security risks, differential adoption rate, lack of awareness and rapidly changing regulations. The study succinctly explains the drivers and detractors to growth engine for Indian fintech landscape.

As per the Nougara hiya et al. (2021), E-commerce market in India is expected to cross \$200B by 2034 overtaking US to become 2nd largest in the world. The study further states that Internet base in India has grown to 52% by 2019 vs mere 4% in 2007. The mobile users are also among the highest in India at 1.13B. The study importantly points out that 22% of the GDP & 8% of total employment is driven through E-tailers.

All the above literature indicates towards a very high growth market for the Indian consumer and research to provide the right product through correct segmentation is the need of the hour.

2.28.1. Customer segmentation in India in Digital & fintech universe

As per Aggarwal et al. (2021), the factor affecting digital payments and cashless transaction modes are Age, Gender, Educational qualification, and Annual Income while it found profession to be a non-significant factor. The research has most samples from Student and employed segment and generally, it has been observed that self-employed customers are averse to using digital payments. A more detailed study would be required to understand the impact of profession.

The study by Shree et al. (2021) supports the above finding and identify demographic factors as major drivers for usages of digital payments in E-commerce. Educated, young, male, with higher income are more likely to use digital payments for e-commerce compared to uneducated, older, female, and lower income customers. Additionally, occupation (Homemaker, student, unemployed are less likely to use

digital payment) and place of residence also plays a significant role in customer propensity for higher digital payments in e-commerce. One significant point to note in this study is its reference to convenience discounting the negative impact of online fraud experience for digital payments. This is in contravention to other studies which puts lot of emphasis on security and trust as major driving factor for Digital payments.

Another study on BNPL customers suggest specific insights for Indian market including that customers with sufficient income are less likely to take BNPL solutions vis-à-vis low-income group. The study also suggest Flipkart pay later; Amazon pay later & Paytm postpaid to be the most used BNPL solution. Flexibility, zero interest, and ability to spread payments have been identified as key factors aiding BNPL while limit knowledge, lack of trust and fear of overleveraging has been identified as key hinderance to the BNPL expansion. The report further identifies that overall BNPL feedback is positive with 49% customers more likely to shop at stores with BNPL solutions and 48% customers trusting BNPL more than cards and loan (Chhabara, 2021)

While the above report highlights that 37% of the customers with sufficient income don't want to use BNPL, another important point to note is that 32% of the customers in this category were keen to use it for higher purchases.

A study by Jaware (2021) suggest that for Indian online consumers, affirmative customer familiarity with the brand is a significant factor for sales in e-commerce marketplace. The study also suggests the product quality in addition to brand is an important factor in Indian online shopping. These findings are significant from our research point of view to understand the affinity of customers to come back for Fintech products from previously used brands.

According to new research by Rashmi and Archana (2021), there has been no significant correlation between Economic class and digital transactions. This study is important due to its implication for fintech products wherein the usage parameters can be made agnostic to customer class.

As per Mittal A (2013), the online shopping provides for the comfort of home & convenience vis-a-vis traditional shopping. The research also suggests the importance of trust and after sales support as major factors for online consumers in India. This research also collaborates with international research about customer behaviour in online shopping in India.

As per Subrato (2017), consumer behaviour for Indian customer is significantly impacted by influence of family, friends and external influencers. The study also note that product comparison is one of the most important factor and customer might have huge post purchase dissonance if the product has disadvantages vis-a-vis competition. While the study was limited by size & time constraints, it sheds light on impact of external influence for the Indian consumers.

2.28.2. Impact of UPI (Unified Payment Interface) on the Indian E-payments

As per the Phone Pe & BCG (2022), India is going through a digital revolution with 40% digital payments driven by UPI which has gained pace due to pandemic and also thanks to the innovative disruptions of new age fintech. The study estimates the digital payments to increase from \$3T in 2021 to \$10T by 2026. India's UPI transactions have increased from 5 billion transactions in FY19 to 46 billion transactions in FY22 as per the report. The study further suggests that the growth in digital payment in India is geographically skewed with higher penetration in southern & western India. The study highlights ONDC, E-Rupee, Super App as areas of future growth in Digital payment and fintech sector.

Another study by Kuriakose et al. (2022) suggests the extended UTAUT2 model for behaviour intention to use UPI and demonstrate its advantages and reason behind surge in customer's intent to

use the technology. The study details Add on services (Positive influence on Behavioural intention to use), Relative advantages (Positive influence on PE & EE), & Promotional benefits (Positive influence on HM, PV & Habits) as extension of other factors.

The study by Ranapriya et al (2021) identifies PE, EE & SI to be the significant factor for intention to use UPI with PE having the highest effect. While the study found an impact of gender & age on SI, the overall effect on intent to use UPI remains gender and age neutral. The study didn't find significant impact of Facilitating conditions in UPI usage.

2.29. Summary of the Literature Review

In the above literature review, a set of studies in the field of Credit Card, BNPL, E-commerce & Customer segmentation have been discussed and while many of the studies have discussed the customer segmentation in these line of business in isolation, there is a general absence of literature on the comparison of segmentation between these products. In single product segmentation also, the segmentation

of fintech is more aligned to e-commerce and differential treatment is missing in most of the research paper.

Table 5: Mode of Purchases wise Customer Segmentation

Study Name	Channel	Year	Impact Points	For / Against	Remark
Kara & Kaynak	Internet Marketing (E-Commerce)	1997	Satisfy Requirements of Individuals	For	While Internet marketing major decision factors include customer loyalty, External influence and convenience, more focus is required to understand the impact of impulse purchase as well as access to funds
Mihova & Pavlov	Commercial Banking	2018	Customer Loyalty	For	
Peppers And Rogers	Internet Marketing (E-Commerce)	2015	Increased Customer Loyalty	For	
Zivile	Internet Marketing (E-Commerce)		Convenience, Simplicity & Better Price	For	
Ul Islam Et Al.	Internet Marketing (E-Commerce)	2017	Positively Associated with	For & against	

	Commerce)		External Influence While Negatively Associated with Carefulness		
José Liébana- Cabanillas Et Al.	Internet Marketing (Commerce)	2014	Positively Associated with External Influence	For	
HDFC Securities	BNPL	2022	Access to credit for NTC	For	There are very limited BNPL research available and indicate mostly on access to credit as the major determinant. More focus is required to understand the impact of customer loyalty and convenience for BNPL customers. Newer studies suggest demographics as important segmentation factors in addition to charges & ability to monitor spends. Not wanting to take debt has been identified as major barrier to BNPL
Payments Journal	BNPL	2021	Limited Access to Credit for Gen Z & External Influence for Millennials	For	
Backman	BNPL	2022	Demographics (Age & Gender)		
PYMNTS	BNPL	2020	Clarity of Fees & Charges & visibility of spends	For	

RFI	BNPL	2022	Not wanting to take Debt	Against	growth
CGI	Credit Card	2014	Loyalty Program & Rewards	For	Most of the Credit Card customers segmentation studies reflect Loyalty program and rewards as the important factors. More understanding is required on customer churn to BNPL and factors impacting this. Additionally, impact of new age customers and distribution channels are not studies in detail
Virtual Incentives	Credit Card	2017	Loyalty Program & Rewards	For	
Umuhoza Et Al.	Credit Card	2020	Loyalty Program & Rewards	For	
Khare Et Al.	Credit Card	2012	Positively Associated with External Influence & Convenience	For	
CRIF-Highmark	Personal Loan	2022	Demographics & Access to Credit	For	
					There are limited personal loan studies and major indicative factors are demographic variables and credit access

In the above literature review, a set of studies in the field of Credit Card, BNPL, E-commerce & Customer segmentation have been discussed and while many of the studies have discussed the customer segmentation in these line of business in isolation, there is a general absence of literature on the comparison of segmentation between these products. In single product segmentation also, the segmentation of fintech is more aligned to e-commerce and differential treatment is missing in most of the research paper.

The current research across Europe & Africa defines factors such as Loyalty program, Generational segmentation, personalized service, access to credit, ease of use as important factor across many of these products.

Additionally, BNPL segmentation academic research within the Indian subcontinent is almost non-existent. Commercial research shows the high growth and potential of BNPL in India with few reports suggesting a strong complementary support for credit card through BNPL based bureau history creation. A more detailed study is required to understand the correct segmentation model in an Indian perspective considering the diversity of ecosystem present. The Islamic banking & Fintech are not allowed in India currently as per the regulatory guidelines despite having 2nd largest Muslim population. If allowed, this will provide for a very robust banking & payment solution especially to underbanked and under-served population. A customer segmentation study is required to understand the possibility of sharia compliant BNPL uptake in Indian context.

2.30. Theoretical Framework

The goal of this section is to build a theoretical framework upon which the research will be based. In the proceeding parts of this section, a brief review of the concepts and of e-commerce and customer segmentation as well as theories relevant for this study will be provided.

2.30.1. Moderating Impact of Digital Payments on E-commerce

Various theories discussed in above literature review reveals that the E-commerce customer behaviour is modified by Digital Payments. Studies by Shamaa et al. (2016) in Jordan, Luong et al. (2022) in Vietnam, have found significant impact of payment on E-commerce. Few of the major pointers which leads to differentiated customer behaviour / segmentation between Digital payment and E-commerce are as follows:

Table 6: E-commerce Modified by Digital Payments

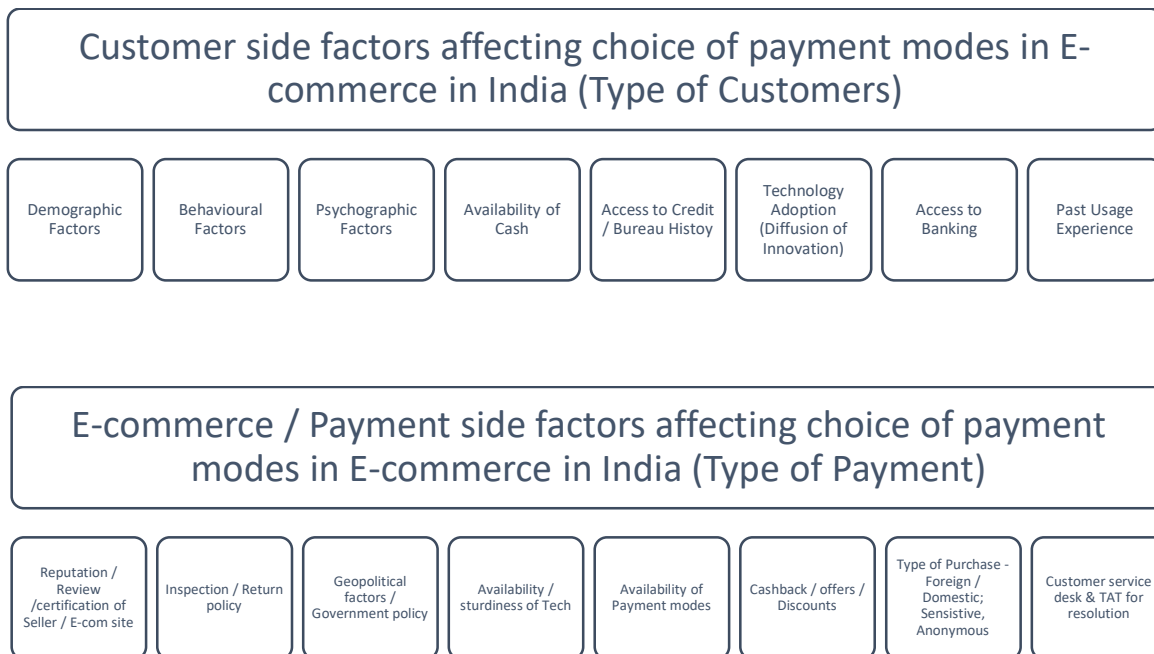
<ul style="list-style-type: none"> Increased trust due to payment instrument familiarity Easier Foreign & complex product purchase Opportunity to purchase on credit through EMI/BNPL Faster checkout / Ease of use / Convenience Loyalty benefits & Cobranding Cashbacks and Discounts 	<ul style="list-style-type: none"> Limited Inspection option Lower Perceived Product certainty Complex return process Security & Hacking threat Technological bottleneck for digital native customers Access to Financial system may be required May require good bureau history Possibility of overleverage
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This modification leads to following impact on E-commerce:

Digital payment Impact on E-commerce	Enhanced Compulsive / Impulsive Buying	Faster checkout (Convenience) Promotions & discounts Increased Perceived Enjoyment
	Reduced pain of payment	Lowered perceived cost Enhanced Trust Ease of use
	Increased Cart Size	Pay Later Option Access to Credit Cashback & Discounts
	Reduced Cart abandonment	Faster Checkout Pay Later / Pay in Part option Enhanced Trust
	Increased Customer Loyalty	Familiarity of payment options Multiple payment options Loyalty programs & Cobranding
	New Purchase opportunities	Foreign portals via CC Financial Inclusion
	Overleverage & Debt trap	Lower Perceived control on Purchase

Figure 6: Impact of Digital Payments on E-commerce

2.30.2. Customer behavioural difference between Payment instruments in E-commerce



Tech affecting choice of payment modes in E-commerce in India (Attributes Model: Moderation by 6A of Tech)

Availability of
supporting
infra

Availability of
Payment
mode

Applicability
of specific
payment
mode

Affordability
of payment
mode

Adaptability
(Tech
adoption rate)

Accessibility
of Payment
mode

Acceptability
for the
payment
mode

Perceived Service Benefit Expectation affecting choice of payment modes in E-commerce in India (pSBE)

Effort
Expectency

Hedonic
Benefits

Social /
Subjective
Norms

Perceived
Security /
Trustworthiness
/ Risk

Performance
Expectency

Perceived cost

Perceived
experience &
Habits

External Factors & Communication affecting choice of payment modes in E-commerce in India (EFC)

Market Rating,
Feedbacks &
Reviews

Advertisement &
External
communication

Word of Mouth /
Inter personal
communication

Geopolitical
factors

Intrapersonal
Communication &
Self Image

New product
launch & Tech
innovation

Neuromarketing
factors

2.30.3. STATE Model for factors affecting Payment Modes in E-commerce in India

Based on the various research reviews, articles & journals, the author has compiled a note on the various UTAUT2 factors and few extended variables affecting different payment modes. The

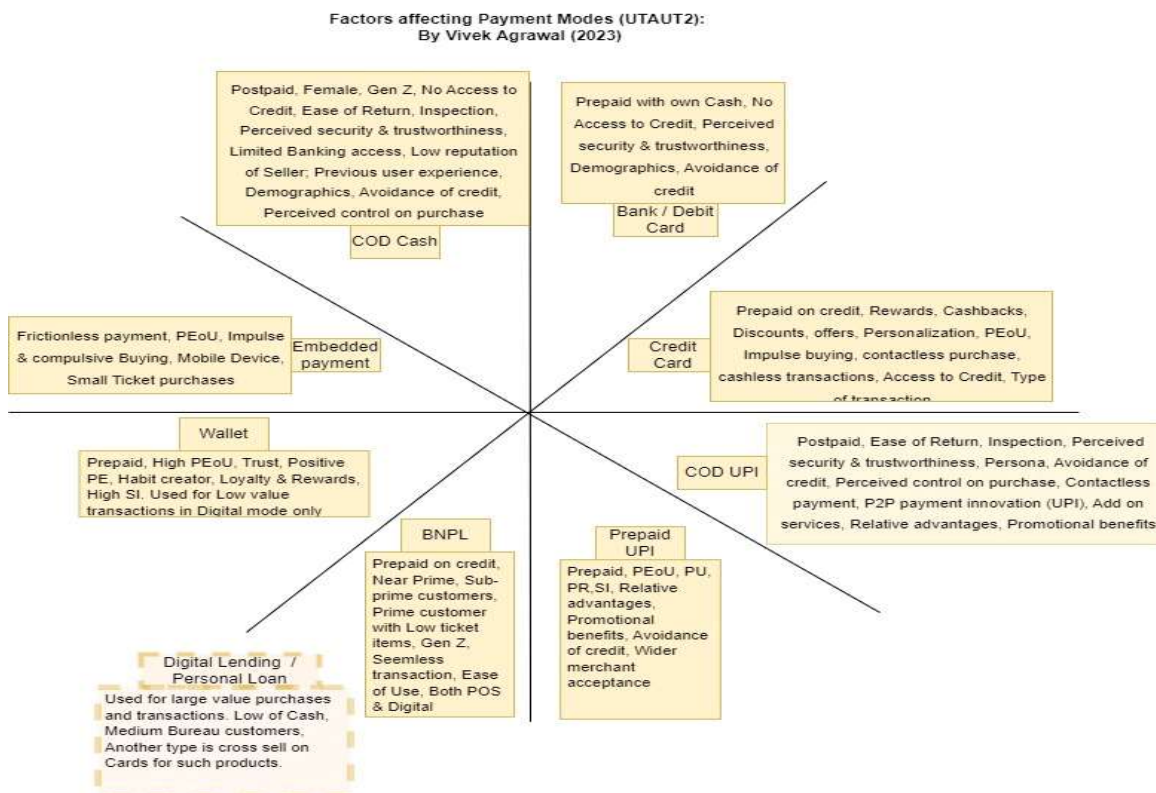


Figure 7:Factor Affecting Payment Mode (Source: Author)
payment modes are either prepaid/postpaid; paid from own money/paid on credit.

2.30.4. Conceptual Model for Choice of Payment Mode in E-commerce Purchases

Here we use the STATE model to explain the choice of payment method in an E-commerce transaction. The model explains the choice of payment methods through the following

2.30.5. TOC (Type of Customer):

This details the effect of following parameters for the choice of payment mode based on the literature review and secondary research:

2.30.5.1. Demographic:

As discussed earlier, Demographics measures a customer propensity based on Age, Income, Gender, Religion, Education etc. The research by Mahavar & Thakur (2018) suggest that the choice of payment method in India depends on the demographics of the customer during festival seasons. Another research by Ray et al. (2023) suggest that gender has a significant impact on usage of UPI in India with male using it more than female customers. Many other researchers have confirmed the impact of demographics in choice of payment method (Cohen and Rysman, 2013; O'Brien, 2022; Merhi et al., 2021; Cabanillas et al., 2014; Petrock, 2021). From the above study, the role of Demographics in choice of payment method is well established.

Additionally, Age has been researched extensively both for intention to use digital payment and customer intention to use online shopping / E-commerce. For Online purchase, Millennials, Gen Z have been understood to be using the E-commerce for shopping more comparatively to Gen X and baby boomers. (Barat, 2010; Metawa et al., 2019; Schewe and Meredith, 2004; Belvaux and Guibert, 2012; Lachhwani & Jain, 2021; Cimperman et al., 2018; Cao et al., 2018).

Also, Age act as moderating factors for other important factors affecting Digital payment and E-commerce.

The research by Upasana et al. (2014) identified that Age, Gender & Education is an important factor for online purchase intention with Millennials (30-45) customers being more likely to make online purchase. Another research by Dahiya (2012) suggested that demographic factors like Age, Gender, Education, Income level, Family size has an influence on purchase decision of customers.

Additionally, the Geographic diversification of customers play a big role in customer intention for both online purchase and digital payment. A study by Kosse & Jansen (2011, 2012) suggest that customer's home location has a significant impact on the choice of payment method. Another study by Suto et al. (2020), suggest that small merchants in Japan wants the payment in cash only.

2.30.5.2. Behavioural

As discussed earlier, customers can be differentiated based on their purchase behaviour and impact of Loyalty, Rewards & Cashback, transactional habits. The behavioural trait of the customer also includes their affection towards brands, benefits sought, occasion, and customer journey stage among others. There has been extensive research to understand the customer intention based on behaviour. The value of transaction greatly affects the choice between cash, debit and credit card with for small value transactions, cash is the choice of payment method (Abdul-Muhmin, 2010; Bounie & Francoius, 2006). Another research by Kemper & Deufel (2018) on large fashion purchase dataset in Europe suggest that customers are more likely to use credit card vs BNPL for their 1st order. Another study by Mishra et al. (2016) suggests that product perception and offers (discounts / cashback) affect customer choice of payment methods with immediate discount on credit card has a higher positive perception compared to cashback.

2.30.5.3. Credit & Risk:

Credit Worthiness, Risk appetite, Debt avoidance, Credit rebuilder

2.30.5.4. Tech Adoption Rate:

Innovators, Early adopters, Early Majority, Late Majority, Laggards

2.30.5.5. Psychographic:

Personality traits, Interest, Social affinity, Attitude, Opinion affect behaviour intention to purchase
As per research by See-To et al. (2014), consumer perception & attitude towards a payment method for offline purchase positively impacts customers online purchase intention using the same payment method. As per Boden et al. (2020), the lower pain of payment with credit card leads to higher purchase propensity and transaction size. As per Sarkam et al. (2022), customer intention to use E-payment is most affected by attitude of the customer towards the payment method. The study further

suggests that any external communication leading to positive attitude will have a positive impact on the customer usage behaviour for E-payment. As per Jumardi et al. (2020), Lifestyle is the most important factor for customers to choose e-wallets, followed by Self-efficacy and trust. The study corroborates the Social Cognitive Theory (SGT: Bandura A, 1979,1982) as well as Consumer Decision model (CDM: Engel-Blackwell-Miniard, 1968) which supports the effect of Psychographic segmentation.

2.30.6. TOP (Type of Purchase):

This details the effect of actual purchase good & the operational requirement on the payment method

2.30.6.1. Category of Purchase:

Domestic or Foreign, Cash or Credit, Postpaid or Prepaid, Paid in Full or Pay in Part.,

2.30.6.2. Value of Purchase:

This is an important factor for the purchase. The payment mode depends on actual as well as the perceived cost of purchase. This has a huge impact on the pain of payment as discussed earlier and leads to the choice of payment mode.

2.30.6.3. Complexity of purchase:

Complexity of purchase as well as the purchase process and operational challenges including ease of return, inspection requirements, and terms of payments among others.

2.30.6.4. Type of online purchase medium:

E-commerce, m-Commerce, Social Commerce

2.31. Attributes of Tech / Attributes of Payment (AOT / AOP):

Irrespective of the desire of customer or the purchase type, in case of absence of tech, the choice of payment mode is constricted significantly. AOT in relation of choice of payment is based on Attributes theory: 6A' theory (Availability of Tech which is further moderated by Acceptability, Affordability, Accessibility, Applicability, Adaptability) proposed by the author earlier in the research in addition to the design aspect i.e., UI/UX.

2.31.1. Accessibility (Device type, Speed & Reliability: Mobile, Desktop, Tablet or IOT)

The choice of payment method is affected by the device type, Speed of internet, browser used, payment intermediaries like Payment service provides, payment networks, loading time and stable connectivity; reliability and payment success rate. As per research by Orimoloye (2022), the device modality significantly affects customers' purchase behaviour with customers using tablet are most likely to purchase, followed by PC & Mobile. Additionally, accessibility of payment method for people with disabilities leads to higher payment adoption rate (Kameshwaran & Muralidhar, 2019)

2.31.2. Acceptability:

Acceptability has an extremely conflicting thought process between customers and merchant. On one hand, merchant would like to cater to cash less method of transaction. The study further suggests that offline penetration of payment instrument affect online acceptability by merchants (Hove & Karimov,2016), the buyer is looking to use COD to ensure payment post-delivery of product only (Wu et al., 2020)

2.31.3. Adaptability:

A study by Lee et al. (2019) suggest that adoption of payment method is contingent to the requirements for both: the consumer as well as that of the retailers getting fulfilled.

2.31.4. UI / UX / CX / Design Complexity:

User Interface, User Experience, Customer experience, and Design Complexity has a significant impact of customer behaviour through Design of medium, ease of navigation, and overall user experience. A payment mode offering seamless integration is likely to have higher Behaviour Intentions. This drives adaptability for the payment modes and significantly affect customer E-commerce purchase intentions.

2.31.5. Availability of Payment modes:

The availability of specific payment mode at the point of purchase is the basic requirement for that particular payment mode to be selected. There is a possibility of unavailability of choice of payment mode affecting the E-commerce purchase decision.

2.32. Service Benefit Perception:

The author identifies and promulgate that the perceived behavioural intentions are affected by various factors including customer's perception towards service benefits. These perceptions are intrinsic to customers and leads to affirmative or negative behaviour intentions. As this makes for a part of the customer complete BI, the author has termed this as Service Benefit Perception / Service Benefit Expectation from a payment mode and shall be using the term throughout the research. The perceived variables affecting adoption of a payment mode are as below (factors are based on UTAUT2 model; for the sake of simplicity, the moderating effect of other factors are negated here as they are well covered under TOC):

2.32.1. Performance Expectancy (PE):

The expected outcome and perceived usefulness of using a payment mode is one of the most important parameters affecting behaviour intention. BI is directly proportional to PE. Factors like pricing, value, convenience, and speed are the major indicator for the construct.

2.32.2. Effort Expectancy (EE):

The perceived complexity of a payment mode usage as well as the extent of effort requirement to complete the payment directly affects the choice of payment mode.

2.32.3. Perceived Cost / Value (PC):

PC is an important factor in choice of payment mode. Any payment mode wherein there is an added cost or the overall value is perceived to higher and pain of payment is perceived to be lower will have higher BI.

2.32.4. Perceived Risk & Perceived Trust (PRPT):

Perceived risk is the associate assumed risk in using a payment mode. Perception of any payment mode with higher hacking threats, risk of fraud, chances of failure and any other type of exposure to systematic and non-systematic risk decreases BI. Perceived Trust is the perceived belief on the trustworthiness of a payment mode. This is affected by affiliations, validations and historical experience of using a payment mode.

2.32.5. Social Influence (SI):

The perception of significant others about the payment mode and their expectation for the individual to use a specific payment mode affect the BI of choice of payment.

2.32.6. Facilitating Condition (FC):

The service benefit expectations for digital payment usage in E-commerce are affected by various support items like customer knowledge, support, security & fraud mitigation tools, organizational policies, and infrastructure.

2.32.7. Hedonic Motivation:

The perceived joy or enjoyment received or experienced while using a service has been defined through Hedonic motivation and custom (er behavioural intention has been indicated to be influenced

by this factor. This has been discussed by various research. For eg. Rodríguez and Trujillo (2013) discussed the role of HM in E-commerce while Khalilah & Indrawati, (2020) highlighted the importance of HM in Digital payments.

2.32.8. Payment Preference:

This is a new construct which has been introduced by the author and this caters to the customer's perception of expected payment preference including availability of preferred payment method, availability of limit & eligibility, and usage pattern for the preferred payment method. This construct is hypothesis to have a strong impact on PE, EE, SI, FC, Trust, HM, SBE, frequency of purchases through various payment modes.

2.32.9. Perceived Experience & Habits:

Experience plays a big role in choice of payment method as a bad experience can lead to avoidance or forbiddance of a payment method for individual. Studies by Krol et al. (2016) suggest that choice of payment method is significantly affected by reward structure, habitual use of specific payment method and bad experiences. The study further details that inconsistency, failure, and glitches in using new technology may lead to total avoidance of the technology by the user. For the purpose of this study, we shall not be using this construct for validation.

2.33. External Factor & Communication:

External factors which are beyond the control of either the customer, merchant, E-comm and digital payment players are covered in this factor. Additionally, the effect of external communication like Advertisement, promotions, campaigns, sponsorship on the choice of payment mode is detailed below. As per Yeh (2021), while technology and social influence leads to customer's cognitive purchase intention; brand equity and public policy along with service quality, service innovation, and switching cost are significant drivers to actual uses vs purchase intentions. EFC also moderates the SBE perceptions for Behavioural intention to use a payment mode. Few of the factors are:

2.33.1. Government Policy:

Any change in government policy may have significant impact on choice of payment. Two of the biggest examples of this are demonetization as well as introduction of UPI in India.

2.33.2. Geopolitical factors:

Geopolitical factors have a significant effect on choice of payment mode especially during international transactions.

2.33.3. Brand Engagement, Advertisements, Campaigns & Sales Promotions (External Communication):

Advertisements play a huge role in creating top of the mind recall and enhancing the wallet share for a particular payment mode.

2.33.4. Interpersonal Communication:

Interpersonal communication factors like Word of Mouth (WOM), feedback, and Review are most important factor for choice of payment mode.

While the model depicts the moderating effect of TOC & EFC on Service Benefit Expectation, we shall not discuss the same in detail here for the same of simplicity, paucity of time and resources.

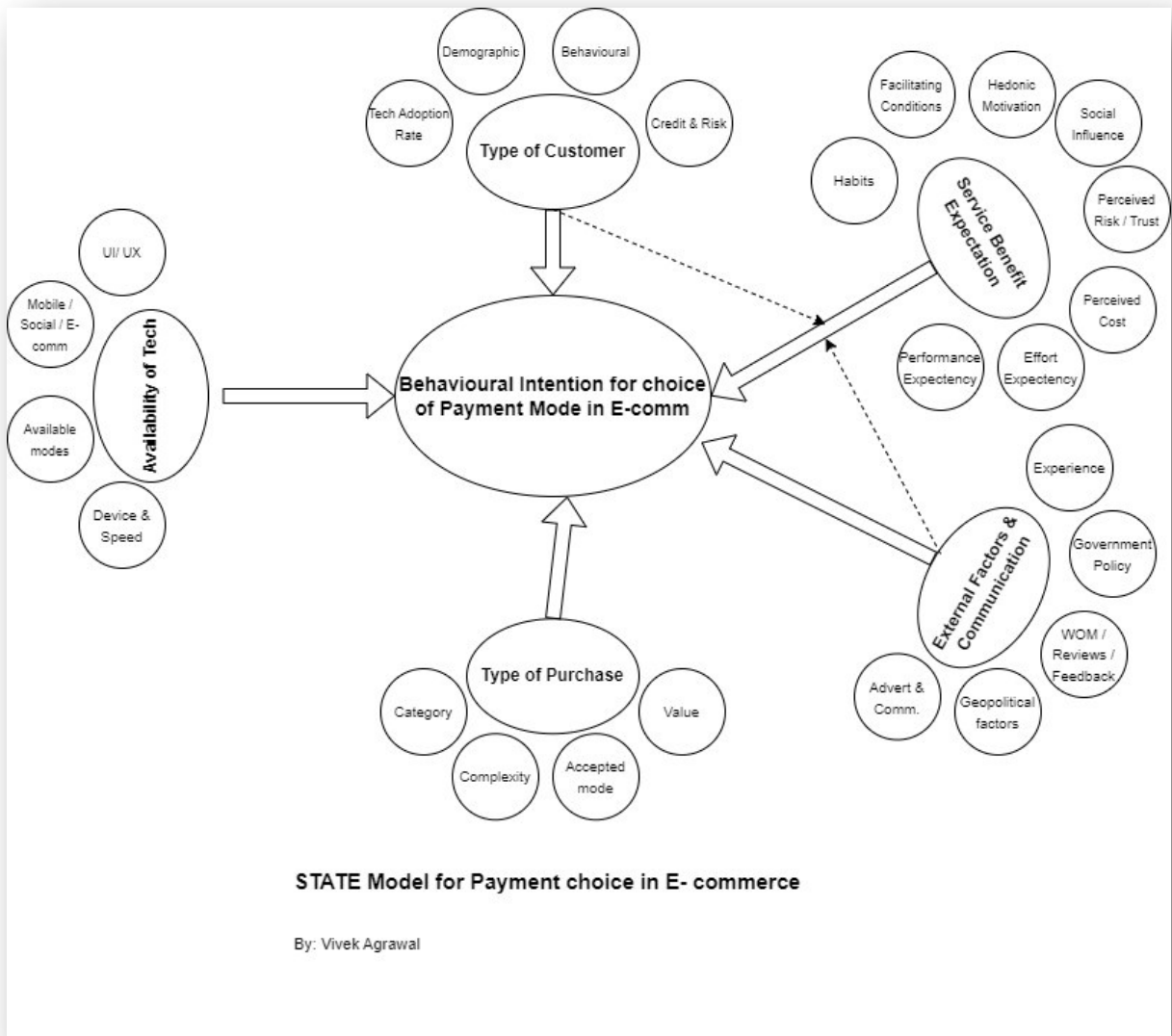


Figure 8: STATE Model for Payment Choice in E-commerce

The further bifurcation for each of these variables are depicted below:

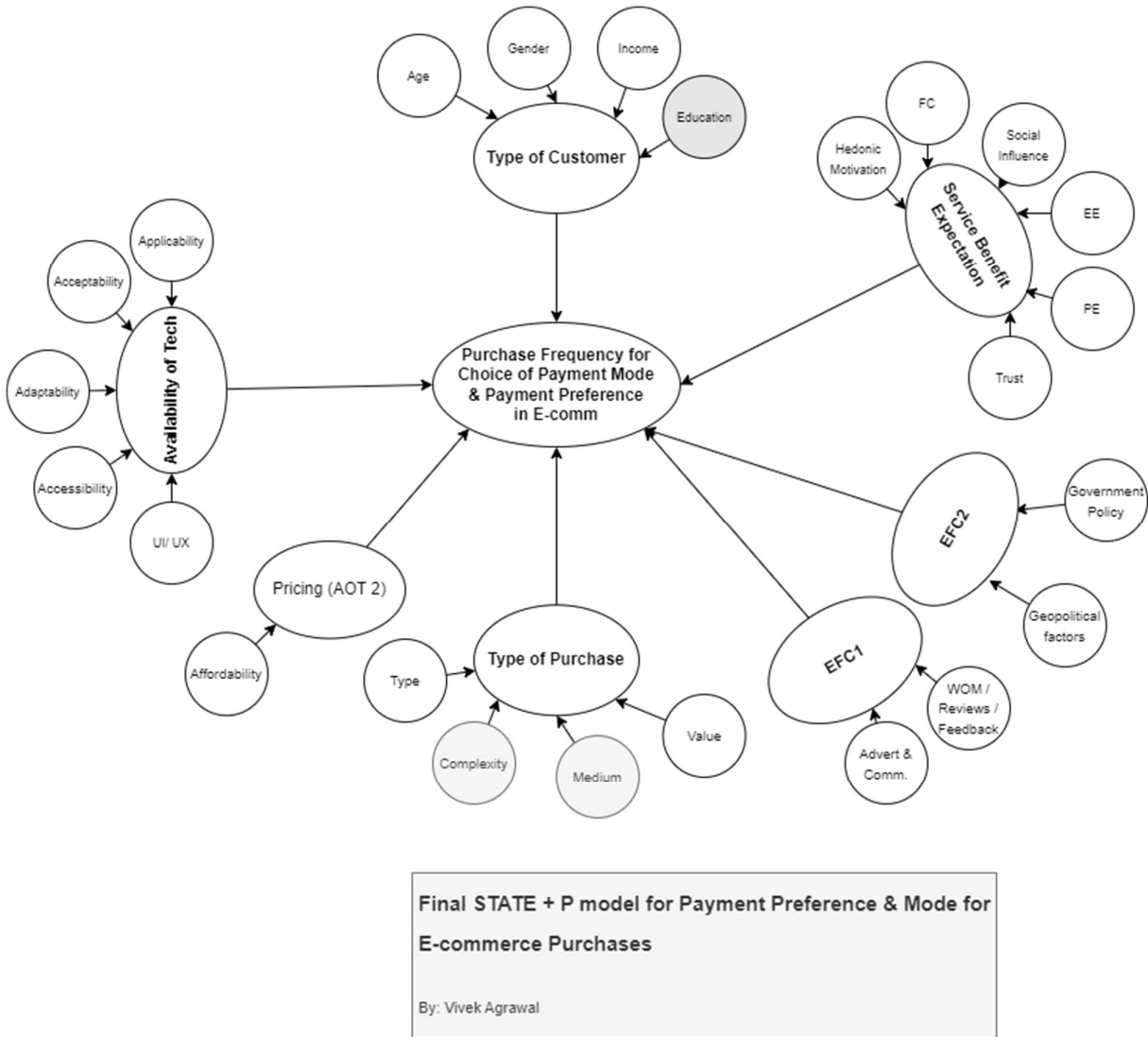


Figure 9: STATE+P Model for Payment Preference

Table 7: STATE Model

Customer Behaviour pointers	Factor	Attribute	Used In Model
TOC (Type of Customer)	Demographic	Age	Yes
TOC (Type of Customer)	Demographic	Gender	Yes
TOC (Type of Customer)	Demographic	Income	Yes
TOC (Type of Customer)	Demographic	Education	No

TOC (Type of Customer)	Demographic	Religion	No
TOC (Type of Customer)	Geographic	Country	No
TOC (Type of Customer)	Behavioural	RFM Transaction	Yes
TOC (Type of Customer)	Behavioural	Rewards	Yes
TOC (Type of Customer)	Behavioural	Discounts	Yes
TOC (Type of Customer)	Behavioural	Loyalty	Yes
TOC (Type of Customer)	Behavioural	Journey Stage	No
TOC (Type of Customer)	Behavioural	Brand Engagement	No
TOC (Type of Customer)	Psychographic	Attribute	No
TOC (Type of Customer)	Psychographic	Personality Trait	No
TOC (Type of Customer)	Psychographic	Interest	No
TOC (Type of Customer)	Credit & Risk Appetite	Bureau score	No
TOC (Type of Customer)	Tech Adoption	Customer Tech Prowess	No
TOP (Type of Purchase)	Category of Purchase	Domestic / International	No
TOP (Type of Purchase)	Category of Purchase	Cash / Credit	No
TOP (Type of Purchase)	Category of Purchase	Prepaid / Postpaid	No
TOP (Type of Purchase)	Category of Purchase	Fashion / Electronics / Grocery / Food App / Travel / Others	Yes

TOP (Type of Purchase)	Category of Purchase	Impulse / Planned	No
TOP (Type of Purchase)	Value of Purchase	Purchase Value	Yes
TOP (Type of Purchase)	Complexity of Purchase	Purchase requiring multiple steps and approvals	No
TOP (Type of Purchase)	Type of Online Purchase Medium	Website / Mobile App/ Superapp / Social Media	Yes
AOT (Attributes of Tech)	UI/UX	UI / UX	Yes
AOT (Attributes of Tech)	Device Type	Medium of purchase	No
AOT (Attributes of Tech)	Acceptability of Payment modes by Merchant	Merchant Acceptance of Payment mode	Yes
AOT (Attributes of Tech)	Availability of Payment mode	E-commerce / Social Commerce / m- Commerce	Yes
AOT (Attributes of Tech)	Ease of Payment	One click payment	Yes
AOT (Attributes of Tech)	Ease of Payment	Ease of payment	Yes
AOT (Attributes of Tech)	Security	High Security	Yes
SBE (Service Benefit Expectation)	PE	Speed / Convenience / Discounts	Yes

SBE (Service Benefit Expectation)	EE	Easy to Learn & Use / Oneclick Payment	Yes
SBE (Service Benefit Expectation)	Pricing Preference	Purchase preference for payment mode	Yes
SBE (Service Benefit Expectation)	HM	Joy & satisfaction for use of payment	Yes
SBE (Service Benefit Expectation)	Trust	Trust on the payment mode	Yes
SBE (Service Benefit Expectation)	Habits	Payment Habits	No
SBE (Service Benefit Expectation)	SI	Subjective Norm / Social Norm	Yes
SBE (Service Benefit Expectation)	FC	Perception of facilitating conditions	Yes
EFC (External Factors & Communication)	Sales Promotion	External sales offer B2B / D2C	Yes
EFC (External Factors & Communication)	Advertisement	External sales offer B2C	Yes
EFC (External Factors & Communication)	Geopolitical	Impact of events like pandemic, war, political, and economic changes	Yes

EFC (External Factors & Communication)	Government Policy	Policies brought in by Government & Government Agencies	Yes
EFC (External Factors & Communication)	WOM/ interpersonal communication	Impact of viral communication & word of mouth	Yes
EFC (External Factors & Communication)	Review / Ratings / Influencer marketing	Impact of customer / external reviews and ratings	Yes

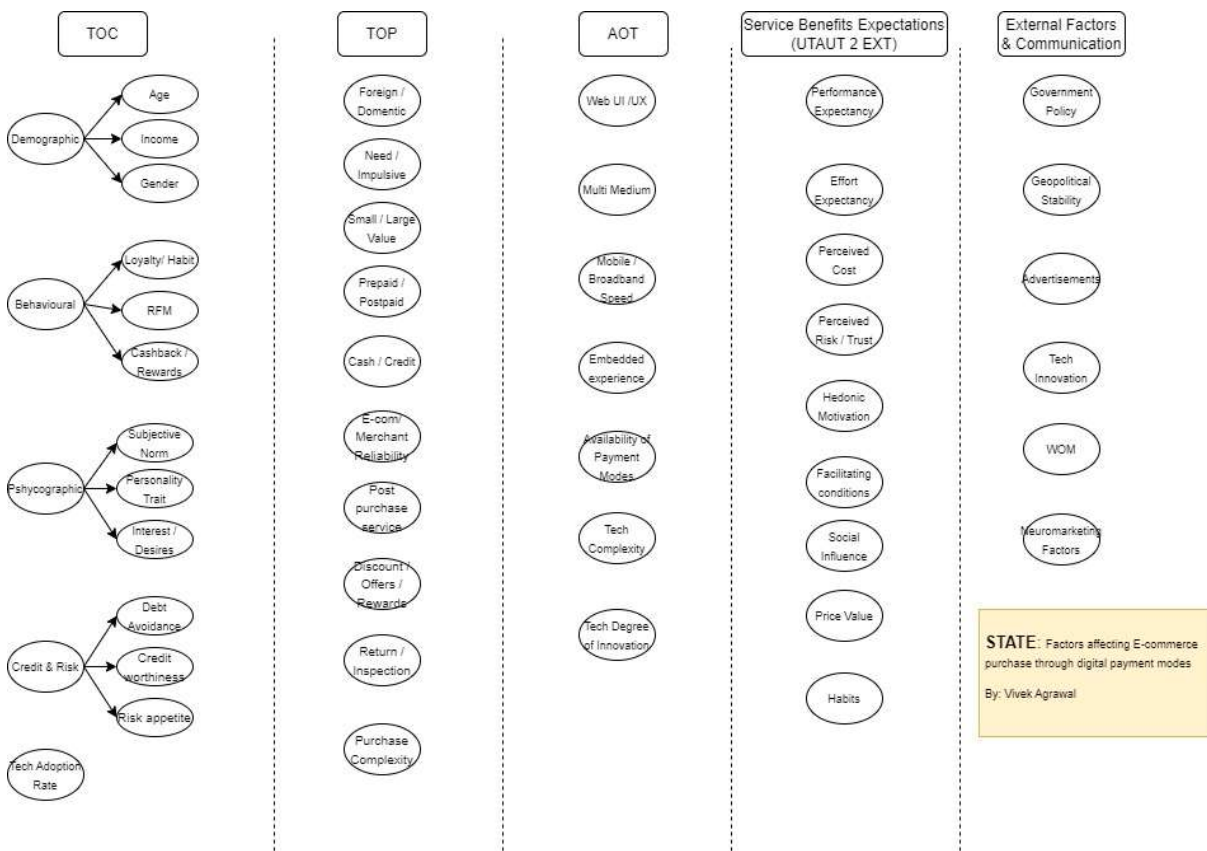


Figure 10: STATE Model Factors

2.34. Proposed Conceptual Model for Moderating Impact of Payment mode on E-commerce transactions

The proposed conceptual model uses extended UTAUT framework. This model denotes that there is a differential UTAUT2 framework for E-commerce & Payment system(s). Based on the previously discussed STATE model, the proposed framework suggests that there is significant impact of Payment preference on each variable of UTAUT2 for E-commerce. Here, each of the variable is affected by a vector load P_x . The model also introduces a direct significant factor of trust for the payment systems on the E-commerce behavioural intention. The effect of External factors & communication is also assumed to be significant for the E-commerce transaction as well as Payment system selection.

An evolved conceptual model which fully describes the compounded UTAUT2 for both E-commerce and Digital payment with moderating effect of choice of Digital payment on E-commerce is as per below diagram. One important point to note in this model is that this model takes the impact of one specific payment mode at one point and doesn't compute intra-dependency and interactivity between the various payment channels individually.

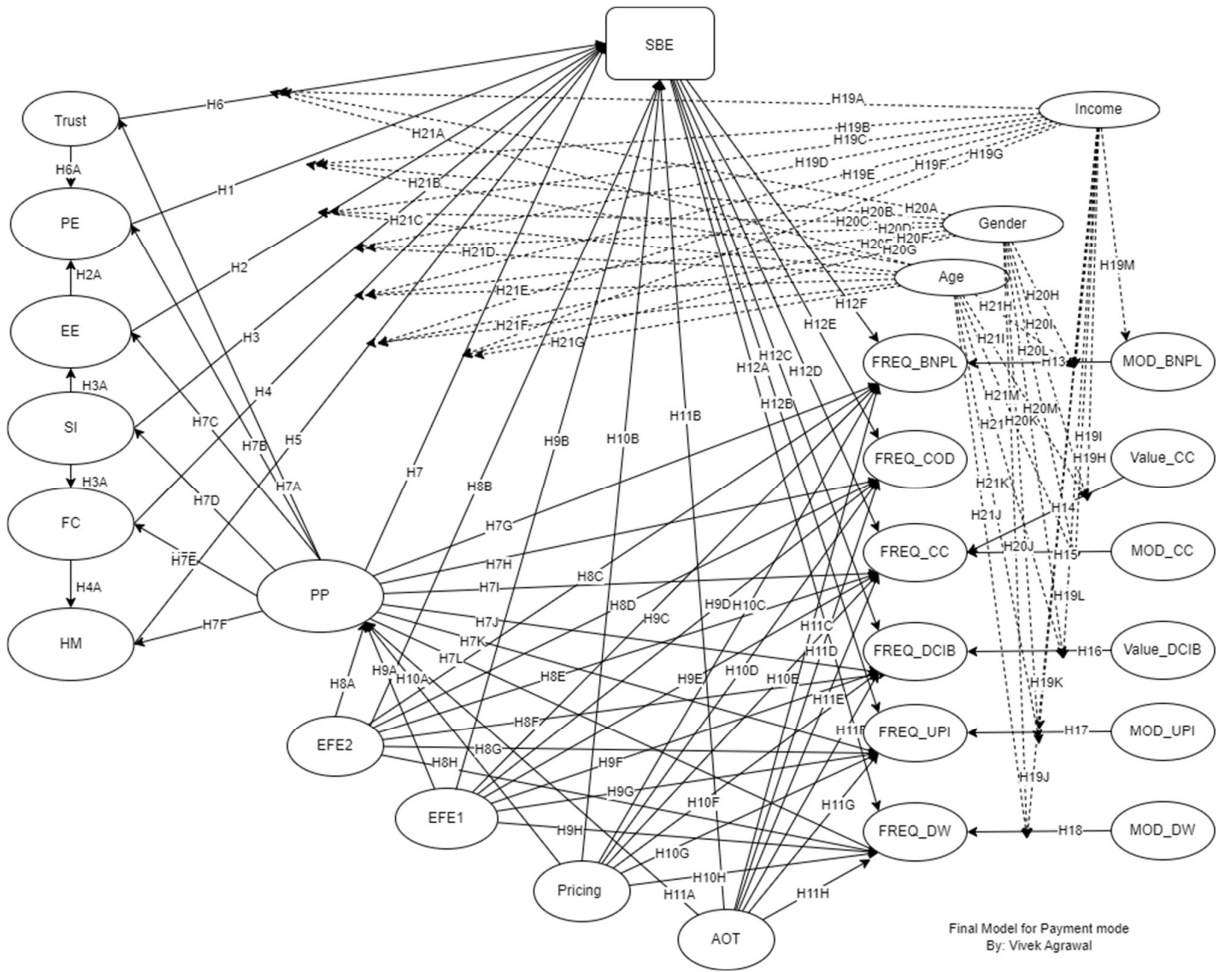


Figure 11: Initial Payment Model for STATE+P

2.35. Hypothesis:

Based on the previous researches across the world, it has been empirically verified that all UTAUT2 factors impacts behaviour intention of E-commerce purchase.

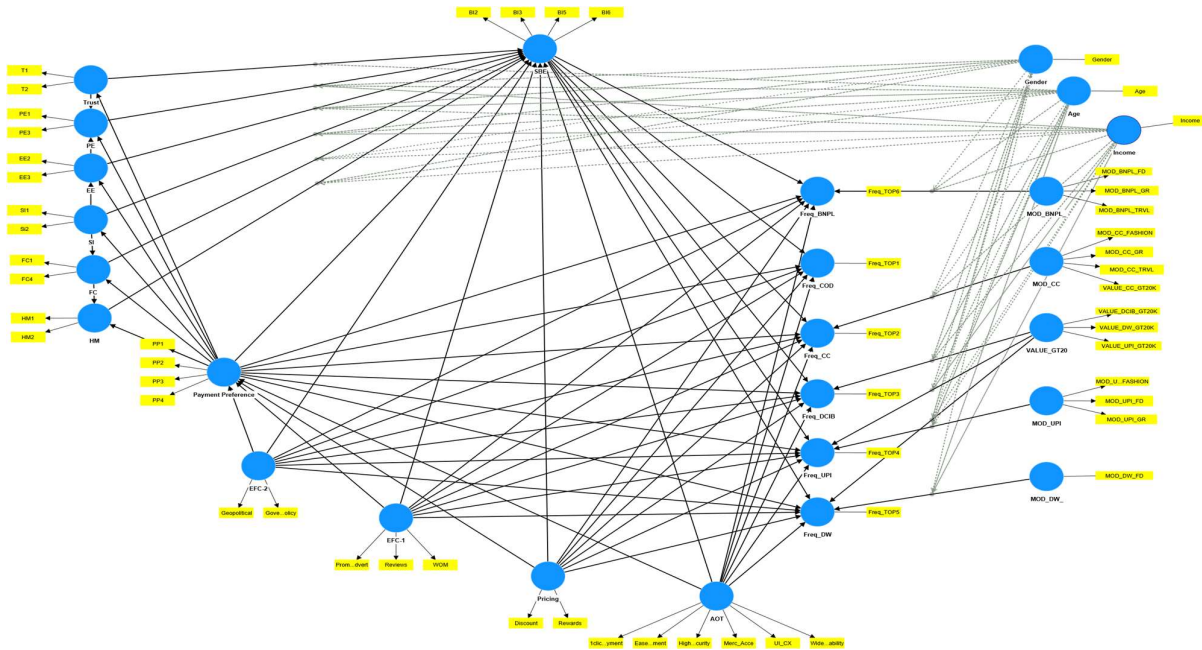


Figure 12: SMARTPLS Model

The proposed model is being presented based on a detailed literature review across various geographies, payment methods, environment and demography. Research by Pushpa et al. (2017), Jain & Chowdhary (2021), Lakhaiyar & Mani (2021) have put additional insight on the factors affecting digital payment adoption in India. Additionally, research by Singh & Rana (2017) and Karthikeyan (2023) have discussed about the role of digital payments in India.

2.35.1. Performance expectancy:

Studies have validated a positive influence of PE on online purchase intention of the customer. The studies have also highlighted a positive impact of PE on intention to use payment mode. PE has also been proved to have been affected by the customer payment preference. There has been various research across the world which points to the positive impact of payment mode on the checkout

process and customer purchase intention. Various research has indicated that PE has a significant impact on choice of payment method and service behavioural expectation (For Eg. Renju and Anju (2019), Meiryani et al. (2022), Alswaigh & Aloud (2021), Koranti & Putri (2019), Mahawadha (2019), Fanuel & Fazar (2021), and Vinitha & Vasantha (2020)).

Based on our extensive literature review, we introduce our conceptual hypothesis:

H₁: PE has a significant impact on SBE for choice of payment method in E-commerce

2.35.2. Effort Expectancy

Studies show that there is a negative relation between Effort expectancy and online purchase intention & E-commerce behaviour of the customer. Many other research has provided empirical details about negative impact of EE on intention to use digital payment. The EE has also been empirically proved to have a moderating effect on choice of payment mode. The ease with which a customer digital payment is done or how seamlessly or effortlessly the transaction is closed helps in faster checkout & lesser dropouts. Various researches indicated that EE has a significant impact on Service benefit expectation for the choice of payment in E-commerce purchases (e.g., Alqudah et al., 2023; Teo et al., 2021; Akhtar et al., 2019; Rahardjo et al. ,2020). Additionally, an empirical studies by Fedorko et al. (2021) also suggest that EE for E-commerce payment has a significant impact on PE.

Through our detailed review of existing literature, we have concluded that

H₂: Effort Expectancy has a significant impact on E-commerce Service benefit expectation

H_{2A}: Effort Expectancy has a significant impact on the Performance expectancy for the choice of payment method in an E-commerce purchase

2.35.3. Social Influence

Thi et al. (2021), Wei et al. (2021), Lian and Yen (2014), Busalim et al. (2021), and Jeon and Ha (2010) have indicated a strong influence of SI on customer behavioural intention for usage of various digital payments when buying online. The researchers have also indicated a strong impact of SI on EE & FC for general E-commerce purchases.

As per the discussed literature review, it has been deduced that Social Influence has a significant effect on the Digital Payments. Additionally, this has also been sufficiently extrapolated that Social Influence is a significant factor EE & FC.

H3: Social Influence has a significant impact on E-commerce service benefit expectation

H3A: Social Influence has a significant impact on Effort expectancy

H3B: Social Influence has a significant impact on Facilitating condition

2.35.4. Facilitating Condition:

Recent studies have identified that Facilitating conditions significantly impact customer adoption of various digital payment modes while making E-commerce purchases. Few of the recent studies confirming the same are Manrai et al. (2021), Leong et al. (2021), Khan et al. (2017), and Widodo et al. (2019). Facilitating condition is also a major driver for extrinsic motivation like availability of infra, support and usage as indicated in the meta-analysis by Tamilmani et al. (2019).

Through an extensive literature review, it can be gleaned that Facilitating conditions has a significant effect on both Payments and E-commerce.

H4: Facilitating Condition has a significant impact on E-commerce purchase intention

H4A: Facilitating Condition has a significant impact on Hedonic motivation

2.35.5. Trust:

As discussed earlier in the research, trust on the payment method plays a strong role in purchase behaviour and service expectation of the customer. This has been discussed and detailed by many researchers including Lizar and Daulay (2021), Sharma et al. (2019), Jumardi et al. (2020), Lee (2006), Lin & Wang (2010), and Nguyen (2016). Additionally, Kim et al. (2009) has indicated that Trust along has direct & indirect impact on Perceived benefits and usefulness of the product.

Based on above analysis, the current research is proposing two hypotheses:

H6: Trust has a significant impact on E-commerce SBE.

H6A: Trust has a significant impact on Performance Expectancy.

2.35.6. Hedonic Motivation:

Hedonic Motivation plays a significant role in E-commerce purchase intention as detailed below. Research by Khatimah (2019), Quin (2021), Melania et al. (2022), Escobar-Rodríguez & Carvajal-Trujillo (2013), and Hassenzahl et al. (2008) have suggested a strong impact of Hedonic motivation on E-commerce payments and payments methods.

H5: HM has a significant impact on customer's digital payment behaviour intentions for E-commerce purchases.

2.35.7. Payment Preference:

This construct has been proposed by the author as the key driver for choice of payment method. As discussed earlier in the research, payment preference has been hypothesised as below:

H7: Payment preference has a significant impact on the Service benefit expectation

H7A: PP has a significant impact on Trust

H7B: PP has a significant impact on PE

H7C: PP has a significant impact on EE

H7D: PP has a significant impact on SI

H7E: PP has a significant impact on FC

H7F: PP has a significant impact on HM

H7G: PP has a significant impact on BNPL purchases

H7H: PP has a significant impact on COD based purchases

H7I: PP has a significant impact on CC based purchases

H7J: PP has a significant impact on Debit Card / Internet Banking based purchases

H7K: PP has a significant impact on UPI based purchases

H7L: PP has a significant impact on Digital wallet based purchases

2.35.8. Pricing

Behavioural variables like Discounts, Offers, Rewards, Loyalty program and points have been clubbed with fees & charges to create a separate construct Pricing. Pricing has a direct impact on Purchase preference and E-commerce SBE. Few noteworthy examples of this are BBD (Big Billion Day) by Flipkart in India and Amazon Prime day across the world. The customers have been found to shift or hold their purchases to extract maximum possible discounts / offers during the period. The customer's payment preference, SBE & actual payment mode usages would also be affected by the reward structure / loyalty benefits in addition to discounts and offers. The Pricing of digital payments moderates the perceived value of product in E-commerce through additional discounting, rewards, offers, and loyalty programs. Research by Zhang (2022), Ching (2008), Taylor (2005), and Carbovalverde (2009) have highlighted the impact of rewards & loyalty points on the payment methods. Additionally, research by Mishra (2016), Hayashi (2012), Stavins (2018), and Kim (2006) have shown the importance of discount on the payment methods especially credit cards. At times, customers have also been found to switch E-commerce sites to avail ongoing payment offers on the specific portals. Based on the above discussion, following hypothesis is being promoted.

There have been various studies which has concluded the significance of this factor.

H8A: Pricing has a significant impact on Payment preference of the customer

H8B: Pricing has a significant impact on the Service benefit expectation of the customer

H8C: Pricing has a significant impact on BNPL purchases

H8D: Pricing has a significant impact on COD based purchases

H8E: Pricing has a significant impact on CC based purchases

H8F: Pricing has a significant impact on Debit Card / Internet Banking based purchases

H8G: Pricing has a significant impact on UPI based purchases

H8H: Pricing has a significant impact on Digital wallet-based purchases

For the model building and based of allied variables, the EFC has been divided into EFC-1 & EFC-2. EFC-1 details the impact of External communication through advertisements, marketing, feedback, WOM and reviews among others. On the other hand, EFC-2 discuss the impact of government policies, and geopolitical factors on the payment preference, purchase intention and actual payment mode usage for purchase.

2.35.9. External Factor & Communication-1 (EFC-1):

Research has consistently shown that advertisements, reviews, word of mouth, and brand image have a significant impact on customer's purchase intention & buying behaviour. Various studies by Monfared (2021), Le (2019), Stefanny (2022), and Dwidienawati (2020) have highlighted the impact of review and word of mouth in detail. At the same time research by Taurino and Handoyo (2023), and Wangsa et al. (2022) have found marketing advertisement to be a significant factor for driving E-commerce purchase intention. Further studies by Rahman et al. (2021), and Gauri et al. (2008) has shown a significant impact of WOM on customer's payment preference.

Based on the discussed literature review, the author proposes the following hypotheses:

H9A: EFC-1 has a significant impact on Payment preference of the customer

H9B: EFC-1 has a significant impact on the Service benefit expectation of the customer

H9C: EFC-1 has a significant impact on BNPL purchases

H9D: EFC-1 has a significant impact on COD based purchases

H9E: EFC-1 has a significant impact on CC based purchases

H9F: EFC-1 has a significant impact on Debit Card / Internet Banking based purchases

H9G: EFC-1 has a significant impact on UPI based purchases

H9H: EFC-1 has a significant impact on Digital wallet-based purchases

2.35.10. External Factor & Communication-2 (EFC-2):

Based on the previous discussed literature review, the author proposes the following hypotheses:

H10A: EFC-2 has a significant impact on Payment preference of the customer

H10B: EFC-2 has a significant impact on the Service benefit expectation of the customer

H10C: EFC-2 has a significant impact on BNPL purchases

H10D: EFC-2 has a significant impact on COD based purchases

H10E: EFC-2 has a significant impact on CC based purchases

H10F: EFC-2 has a significant impact on Debit Card / Internet Banking based purchases

H10G: EFC-2 has a significant impact on UPI based purchases

H10H: EFC-2 has a significant impact on Digital wallet-based purchases

2.35.11. Attributes of Tech (AOT):

Earlier in the literature review, it was indicated that customer's digital payment preference, purchase intention and actual purchase using a payment mode is affected by customers perception of various

attributes of tech including, one-click payment, high security, ease of payment, UI/UX, widespread availability, and merchant acceptability.

Based on the previous discussed literature review, the author proposes the following hypotheses:

H11A: AOT has a significant impact on Payment preference of the customer

H11B: AOT has a significant impact on the Service benefit expectation of the customer

H11C: AOT has a significant impact on BNPL purchases

H11D: AOT has a significant impact on COD based purchases

H11E: AOT has a significant impact on CC based purchases

H11F: AOT has a significant impact on Debit Card / Internet Banking based purchases

H11G: AOT has a significant impact on UPI based purchases

H11H: AOT has a significant impact on Digital wallet-based purchases

2.35.12. Type of Payment:

Type of Payment method and value of purchase for various purchase category as a significant factor for choice of payment has been discussed by various researchers. The study by Singh & Srivastava (2018) suggests significant role of product type on frequency of online purchase. Research by PYMNTS (2020, 2022), Bain (2021), Cardify.ai (2021), TSG (2022), Muhn (2022), Fiori et al. (2014), Klee (2008), and Khare et al. (2012) have discussed the significance of type of purchase on choice of payment method. Sari (2021) through research in Indonesia suggests that payment mode for BNPL has a significant impact on the purchasing behaviour.

Based on the above discussion, this thesis proposes the following hypotheses:

H12: Mode of Payment for various type of purchase has a strong impact on frequency of BNPL payment method

H13: Value of Purchase for various type of purchase has a strong impact on frequency of BNPL payment method

H14: Value of purchase for various purchase type has a strong impact on frequency of CC as payment method

H15: Mode of Payment for various purchase type has a strong impact on frequency of CC as payment method

H16: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of DCIB payment method

H17: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of UPI payment method.

H18: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of DW payment method.

H18A: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of COD payment method.

2.35.13. Demographics (Age, Income, Gender):

There are various studies which finds a substantial effect of age, gender and income as a factor / moderator in intention to use digital payment methods (Daulay, 2021; Hilmawan et al., 2022; Lohana & Roy, 2021; IJITEE,2021; Mishra et al., 2020). As per K. Leppel, D. McCloskey (2011), older customers have higher security concern and ease of use while using E-commerce as compared to younger customers. As per Guhan & Nigama (2022), Social influence, Effort expectancy, and Performance expectancy is moderated more by Gen X for adoption of E-Wallet. Research by See-To et al. (2014) suggest the moderating role of income in customer behavioural intention for payment technology in online purchase. Additional study by Acheampong et al. (2018) in Ghana suggest the role of gender in moderating the behavioural indicators for payment method. Lian (2014) suggest that

PE & SI are moderated by age and has major impact for older customers. The study by Kalia (2017) indicates a strong relationship between Gender and frequency of purchase, while another study by Pascual-Miguel et al. (2015) indicates the moderating role of gender on the impact of product type on online purchases. Research by Law (2016) suggest that users aged 41-50 have higher perceived ease of purchasing compared to elder customers.

Through the extensive literature review we can corroborate that:

H19A: Income has a significant impact on SBE

H19B: Income act as significant moderator to the effect of Performance expectancy on SBE

H19C: Income act as significant moderator to the effect of Effort Expectancy on SBE

H19D: Income act as significant moderator to the effect of SI on SBE

H19E: Income act as significant moderator to the effect of FC on SBE

H19F: Income act as significant moderator to the effect of HM on SBE

H19G: Income act as significant moderator to the effect of Payment Preference on SBE

H19H: Income act as a significant moderator to the effect of value of purchase on frequency of CC Purchase

H19I: Income act as a significant moderator to the effect for various type of credit card purchases on frequency of CC Purchase

H19J: Income act as a significant moderator to the effect for the various type and value of DW purchases on frequency of DW Purchase

H19K: Income act as a significant moderator to the effect for the various type and value of UPI purchases on frequency of UPI Purchase

H19L: Income act as a significant moderator to the effect for the various type and value of DCIB purchases on frequency of DCIB Purchase

H19M: Income act as a significant moderator to the effect of type of purchase through BNPL on frequency of BNPL purchase

H20A: Gender act as significant moderator to the effect of Trust on SBE

H20B: Gender act as significant moderator to the effect of PE on SBE

H20C: Gender act as significant moderator to the effect of EE on SBE

H20D: Gender act as significant moderator to the effect of SI on SBE

H20E: Gender act as significant moderator to the effect of FC on SBE

H20F: Gender act as significant moderator to the effect of HM on SBE

H20G: Gender act as significant moderator to the effect of Payment Preference on SBE

H20H: Income act as a significant moderator to the effect of value of purchase on frequency of CC Purchase

H20I: Gender act as a significant moderator to the effect for various type of credit card purchases on frequency of CC Purchase

H20J: Gender act as a significant moderator to the effect for the various type and value of DW purchases on frequency of DW Purchase

H20K: Gender act as a significant moderator to the effect for the various type and value of UPI purchases on frequency of UPI Purchase

H20L: Gender act as a significant moderator to the effect for the various type and value of DCIB purchases on frequency of DCIB Purchase

H20M: Gender act as a significant moderator to the effect of type of purchase through BNPL on frequency of BNPL purchase

H21A: Age act as significant moderator to the effect of Trust on SBE

H21B: Age act as significant moderator to the effect of PE on SBE

H21C: Age act as significant moderator to the effect of EE on SBE

H21D: Age act as significant moderator to the effect of SI on SBE

H21E: Age act as significant moderator to the effect of FC on SBE

H21F: Age act as significant moderator to the effect of HM on SBE

H21G: Age act as significant moderator to the effect of PP on SBE

H21H: Age act as a significant moderator to the effect of value of purchase on frequency of CC Purchase

H21I: Age act as a significant moderator to the effect for various type of credit card purchases on frequency of CC Purchase

H21J: Age act as a significant moderator to the effect for the various type and value of DW purchases on frequency of DW Purchase

H21K: Age act as a significant moderator to the effect for the various type and value of UPI purchases on frequency of UPI Purchase

H21L: Age act as a significant moderator to the effect for the various type and value of DCIB purchases on frequency of DCIB Purchase

H21M: Age act as a significant moderator to the effect of type of purchase through BNPL on frequency of BNPL purchase

H22: Choice of payment has a moderating impact on both Online purchase intention and online purchase behaviour.

CHAPTER 3: RESEARCH METHODOLOGY

3. RESEARCH METHODOLOGY

3.1. Overview

The definition of Research as per Woody (1927) is

“Defining and redefining problems, formulating hypothesis or suggested solutions; collecting, organising and evaluating data; making deductions and reaching conclusions; and at last, carefully testing the conclusions to determine whether they fit the formulating hypothesis”

Kothari (2006), explains the definition of Research Methodology as the scientific process to understand how the research is done. Research methodology aims to study the underlying research method and motive behind choosing the particular method.

This section deals with creating a research plan to discuss the research Methodology, Research Methods, based on the identified research problem, various research questions, and objectives are decided. This research usages descriptive & exploratory analysis for its study using quantitative method.

The primary research for this study is conducted through empirical data collections from fintech customers who are using various payment methods (BNPL, Credit Card, Personal Loan, Digital Lending & Digital Wallet) and COD / Bank to make E-commerce payments in India. For the purpose of this research, a mixed methodology is adopted with three different methods to:

1. Based on the descriptive details from the datapoints collected, a RFM analysis is done and RFM score is calculated for each dataset. This RFM score is cross-tabbed with demographic variables like Age, Income, and Gender to identify impact of these variables on behavioural intensity on online purchases.

2. A conceptual model is created based on the extensive literature review for factors affecting choice of payment methods for an ecommerce transaction. This model uses customer segmentation theories like demographic, and behavioural segments to define Demographic & Pricing construct, diffusion of innovation theory to define AOT variables & UTAUT2 model to introduce Service Benefit Expectation (SBE) by assimilating the impact of BI with other model constructs in the framework.
3. This conceptual model is tested using extended UTAUT2 with constructs PE, EE, SI, FC, HM along with moderators like Age, Gender, and Income (Venkatesh et al., 2010). Additionally, constructs PP (Payment preference), EFC-1, EFC-2, Pricing, and AOT. The customer's behaviour intention to use a payment method in E-commerce purchase is used to test the significance for frequency of purchases using various payment methods. This reflective construct is also impacted by customer's intention to use the specific mode and value of purchase. The effect of all the dependent variables on purchase frequency for various payment method is also tested and validated. This effect is also assumed to be moderated by Age, Gender, and Income. Indicator items for all the constructs were modified to accommodate the impact of payment method on E-commerce and thus the construct reliability & validity was tested in detail to scale validation.
4. To identify and classify the various variable indicators for mode and value of purchases, clustering methods of KM Clustering is used & for first level grouping of variable indicators to the construct, Hierarchical clustering method is used. The method used is iteration method with six clusters. KM helps to identify principal variables from existing variables for payment modes as well as E-commerce. This cluster is cross validated through Hierarchical clustering. For Hierarchical clustering, Average linkage, and Agglomerative method is used. The proximity matrix and dendrogram is used to identify the strength of relationship between the variables within the cluster. The research methodology used is K-mean / Hierarchical clustering for identification of segment centres for various Payment

Instruments and their relative distance from the E-commerce variables. KM clustering is done on specific set of variables to identify the nearest neighbours.

5. Once customer segments are identified and defined then PLS-SEM (Heir et al. 2010) has been used to identify the relationship strength between segments and their distance from each other for both observed and latent variables. The constructs of the model are validated through bootstrapping for significance and PLS Predict for future implementation. The model is also checked for impact of redacted variables through gaussian copula.

Additionally, importance performance map analysis was done to understand the importance of various construct and indicators on various targeted dependent variables. Based on these, a redefined framework is created with all significant indicators & construct. The construct is checked for reliability, validity, multicollinearity, VIF, discriminant validity, bootstrapping, predictability, and endogeneity. The model was first tested using a pilot study, and once the results are found to be corroborative, the survey was sent to all the other respondents.

6. An alternate model with same constructs were also tested wherein the impact of BI for E-commerce purchase using a payment method on the payment preference of the customer is tested.

3.2. Population and Study Sample

The general population is the total customer universe using any of the payment product for E-commerce & POS in India. The target population for the research is customer base of BNPL, Credit Card, Digital Lending, Digital Wallet, & Personal Loans in Indian market. The survey population is the customer base for these products in Metros & Tier II cities whose response is expected to collected online through a survey questionnaire.

3.3. Sample Size and Selection of Sample

A sample size of 359 customers was used. The sample selection ensured gender neutrality as well as avoidance of sampling biases especially under coverage and voluntary response bias. The sample was collected through an informed questionnaire from online users across Indian cities to ensure avoidance of location, gender and cultural bias. The survey was sent initially to 35 respondents for validating the survey and based on their affirmative feedback and corroborative result, the survey was shared with other respondents.

3.4. Sources of Data

As per the Instrument design, the research needs to identify and describe the source of data collected, i.e., through in person data collection (Focus interviews, Group discussions, Telephonic discussions), Mail Surveys, or online research (Fink 2006; Sekaran 2003). Each of these methods have their pros and cons and the author has to decide on the best method depending on available resources, time constraints, researcher skillsets and the participants diversity (Sekaran, 2003). Primary data collection has been done using survey questionnaire from sample population. Available software like Survey Monkey was envisaged to be used to create the questionnaire.

The Survey was created using Qualtrics (<http://www.qualtrics.com>) with the help of the survey wizard provided in the portal. The survey has been created using anonymous link. The questions were created based on the literature review, insights from peer group, and existing scales. Survey questions construed of 16 Nominal, 15 ordinal, and 40 Likert scale indicators. Two group of survey questions on mode of payment and medium of purchase for various purchase type were collected as multiple selection type.

3.5. Collection of Data

Data used for this study was collected between 27th Sep 2023 and 30th Oct 2023. Customer segmentation data was collected through Survey of E-commerce customers in India using various

payment method using a mix of 7-point Likert scale, binary scale, and ordinal scale for the taking the customer feedback. The survey scales was taken from existing research like Venkatesh et al. (2010), product features, and author proposed additional constructs. Data collection was done through random sampling of online users with an aim to maintain data neutrality. Links were shared through whatsapp, Email & reference communication for getting the survey filled. A total of 500+ links were sent to random group of people out of which 359 responses were recorded.

3.6. Data Cleaning & restructuring

Data cleaning is a process of handling missing datapoints, fixing structural issues, and data validation for the model created. The survey data which is collected, was checked for the missing value and in 57 cases, no value other than the initial control variables were found to be present. These data points were removed and out of remaining 302 datapoints, it was checked for outliers and 67 additional datapoints were found to contain extreme outlying values and thus redacted. The remain 235 datapoints were checked and validated for various constructs and model fit. Another 34 datapoints were removed to ensure reliability and validity of the model along with discriminant validity. This has led to a cleaned data sample size of 201 datapoints on which the data analysis is done. For validation and model fitment, multiple selection question for mode of payment was converted to binary data with each mode of payment for a specific purchase type created as a category. Considering the large set of variables and high number of missing values in medium of purchase construct, it was not considered for the analysis.

3.7. Data Analysis Software

Data analysis was done using software including SPSS, SmartPLS4, R, and Microsoft Excel. Additionally, a basic insight on the collected data was also provided by the Qualtrics portal and the same has been taken into consideration for data feedback.

3.8. Ethics and Human Subjects Issues

All Ethical standards was followed and the data was collected with prior information and consent of participating individuals.

CHAPTER 4: RESULTS

4. ANALYSIS AND RESULT

Based on the research done through detailed literature review and quantitative data, the analysis is presented in three parts:

4.1. Descriptive Statistics

A total of 359 responses were received within the survey period. While the effort was put to collect a gender neutral, location, occupation, and education agnostic data, based on the anonymous survey, following data points were collected.

4.2. Demographic & Geographic

- a) Gender: Total of 354 respondent declared their age with 69% (245) as male and 31% (108) respondent as Female.
- b) Age: The survey age distribution has a mix of GenZ (52%) and Millennials (40%) while the remaining is contributed by Gen X & Baby Boomers, with a small number constituting of Gen Alpha. The distribution is relatively even for Male compared to Female respondents wherein the skewness is towards the Gen Z.

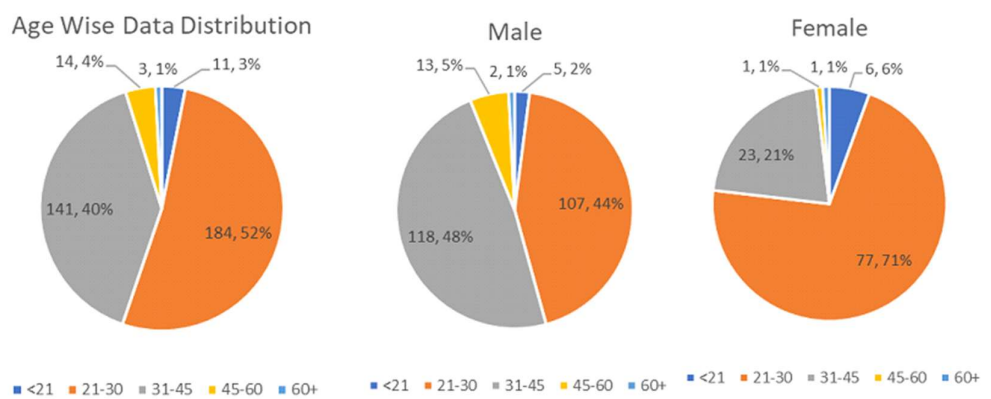


Figure 13: Age impact on Payment Methods

- c) **Income:** In literature review, income was found to be one of the most important factors for the E-commerce payment method propensity. The current survey has a decent mix of responses with 43% of the respondents having <5L income, 24% are having an income of 5-10L, 17% having 11-25L household income, 13% having 25-50L income and remaining 3% of the respondents having household income of 50L+.

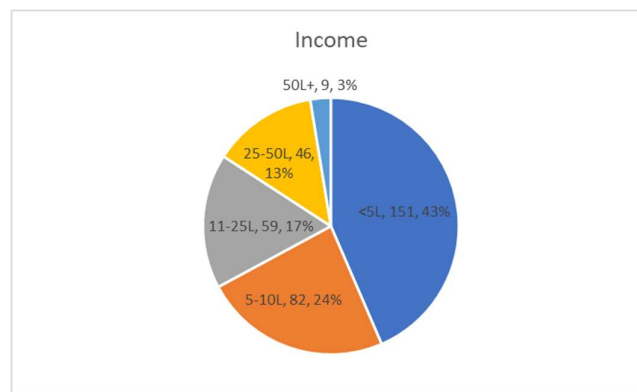


Figure 14: Income impact on Payment methods

In addition to above, few of the demographic & Geographic variables were recorded but not used in the analysis due to reasons like high skewness, time, and resource paucity.

- d) **Geography:** 93% of the respondents were from urban location with maximum response from Bangalore, India location. As the total count is highly skewed this variable is not considered for the analysis.
- e) **Occupation:** 88% of the responses received was from salaried segment and hence this variable was also not considered for the analysis.

- f) **Education:** 77% of the respondents were UG+ (64%) & Professionals (13%). 20% of the responses were received with education level of XI-UG, while remaining 3% were having an education of Class X and below.

4.3. Behavioural

4.3.1. RFM:

Recency: The collected data has 40% of the respondents confirming an e-commerce transaction within one week of survey taken, 21% have done at least one transaction in 1W-1M period, 10% have done a transaction in 1M-3M period, while 7% have done the transaction in 3M-12M period. A good 22% of the respondents haven't done any transactions in last 12M. The Recency dummy variable was created by reversing the counts (Subtracting all scores from 6 to reverse the order to ensure recent transactions have the highest score).

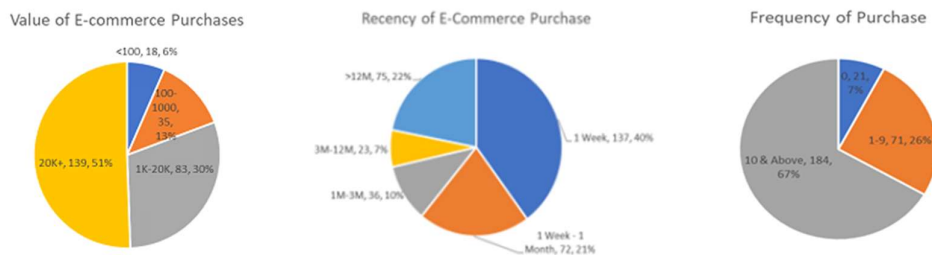


Figure 15: RFM Model

- g) **Frequency:** The frequency of E-commerce purchase has been derived by creating a dummy variable wherein the highest frequency across all payment modes is accumulated. Based on this, the frequency of E-commerce purchases among the respondents are as below: 67% of the respondents have done 10 & more transactions

within last 12 M, 26% of the respondents have done a transaction between 1-9 while rest haven't done any transactions in last 12M for E-comm purchases.

- h) **Value (Monetary):** The value of E-commerce purchase has been derived by creating a dummy variable wherein the highest value across all payment mode for a customer is recorded. Based on the this, the value of purchase among the respondents who provided a valid output are as follow: 51% of the respondents have done a purchase of 20K+ in last 12M, 30% have done a transaction of 1K-20K, 13% have done the monetary transaction of Rs 100-1000, and remaining 6% have done a transaction of less than 100 Rs out of total valid response of 275.

In creation of dummy variable for Value & Frequency of E-comm purchases, it is assumed that the total sum score for all categories will lie in the same category considering the non-linear nature of the category creation. Additionally, a detailed clustering has been done for value of purchases for specific purchase type along with the mode of purchase using hierarchal clustering & K-Mean clustering for revalidation. Frequency of the transaction has been used in detail as the outcome variable and its significance has been checked for various payment mode. Other behavioural variables like Rewards, Discounts, loyalty programs & point, and offers have been clubbed along with Fees / Charges to create Pricing.

RFM Analysis: Post calculating the values for Recency, Frequency, and Monetary value for all the respondents, RFM analysis is done using weighted average method with equal weights assumed for all the parameters.

Table 8: RFM Values of Respondents

RFM Value	Total Respondents
3	6

For the RFM category cross tab with Income, this can be easily seen from the data that for higher income the E-commerce promoter propensity is very high, while lower income respondents are more user category. Based on this we can propose that income has a strong relationship with E-commerce purchase propensity.

Table 10: RFM Score Income Wise

RFM/Income	<5L	5-10L	11-25L	25-50L	50L+	Total
11-12	14%	35%	78%	80%	83%	40%
3-4	7%	0%	0%	0%	0%	3%
5-7	29%	18%	2%	3%	17%	18%
8-10	51%	47%	20%	17%	0%	39%
Total	100%	100%	100%	100%	100%	100%

For the RFM score & Gender crosstab analysis, it can be seen that there is marked difference between Male & Female when it comes to RFM Scores and accordingly in their E-commerce purchase propensity. 44% of the Male respondents are promoters compared to 31% of Female, while 30% of the female are Moderate users compare to 13% of Male respondents.

Table 11: RFM Score Gender Wise

RFM / Gender	Male	Female	Total
11-12	44%	31%	40%
3-4	4%	1%	3%
5-7	13%	30%	18%
8-10	39%	38%	39%
Total	100%	100%	100%

K-Mean Clustering

For identification of clusters in Mode of payment and Value of Payment, K-Mean Clustering is used for each type of payment mode.

For COD: Only one final cluster could be derived with Mode of Payment as COD for Electronics, Food delivery, and Fashion, along with value of payment between 100 to 1000Rs.

Table 12: K-Means Mod v/s Value for COD

	Initial Cluster Centers	
	1	2
MOD_COD_ELEC	0	1
MOD_COD_GR	0	1
MOD_COD_FD	0	1
MOD_COD_TRVL	0	1
MOD_COD_Fashion	0	1
MOD_COD_Others	1	0
VALUE_COD_LT100	1	0
VALUE_COD_100_1K	0	1
VALUE_COD_1K_20K	0	0
VALUE_COD_GT20K	1	0

Iteration History^a

Iteration	Change in Cluster Centers	
	1	2
1	1.334	1.173
2	0.070	0.101
3	0.038	0.049

4	0.012	0.015
5	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 5. The minimum distance between initial centers is 3.000.

Final Cluster Centers

	Cluster	
	1	2
MOD_COD_ELEC	0	1
MOD_COD_GR	0	0
MOD_COD_FD	0	1
MOD_COD_TRVL	0	0
MOD_COD_Fashion	0	1
MOD_COD_Others	0	0
VALUE_COD_LT100	0	0
VALUE_COD_100_1K	0	1
VALUE_COD_1K_20K	0	0
VALUE_COD_GT20K	0	0

Number of Cases in each Cluster

Cluster	1	114.000
	2	87.000
Valid		201.000
Missing		0.000

For CC: For CC, when various variables of mode of payment and value of payments using credit card is iterated through KMC, all mode of payments except for other type of purchase, and those for value of purchase greater than 1K (Value_CC_1K_20K, Value_CC_GT20K) were found to be of part of the cluster two and driving uptake. This is changed from the initial cluster wherein all the variables are part of cluster two.

Table 13: K-Means Mod v/s Value for CC

Initial Cluster Centers

	Cluster	
	1	2
MOD_CC_ELEC	0	1
MOD_CC_GR	0	1
MOD_CC_FD	0	1
MOD_CC_TRVL	0	1
MOD_CC_FASHION	0	1
MOD_CC_Others	0	1
VALUE_CC_LT100	0	1
VALUE_CC_100_1K	0	1
VALUE_CC_1K_20K	0	1
VALUE_CC_GT20K	0	1

Iteration History^a

Iteration	Change in Cluster Centers	
	1	2
1	0.828	1.249
2	0.188	0.204
3	0.098	0.114

4	0.015	0.018
5	0.015	0.019
6	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 6. The minimum distance between initial centers is 3.162.

Final Cluster Centers

	Cluster	
	1	2
MOD_CC_ELEC	0	1
MOD_CC_GR	0	1
MOD_CC_FD	0	1
MOD_CC_TRVL	0	1
MOD_CC_FASHION	0	1
MOD_CC_Others	0	0
VALUE_CC_LT100	0	0
VALUE_CC_100_1K	0	0
VALUE_CC_1K_20K	0	1
VALUE_CC_GT20K	0	1

Number of Cases in each Cluster

Cluster	1	111.000
	2	90.000
Valid		201.000
Missing		0.000

For DCIB: All types of purchases except others are mapped through this.

Table 14: K-Means Mod v/s Value for DCIB

Initial Cluster Centers

	Cluster	
	1	2
MOD_DCIB_ELEC	0	1
MOD_DCIB_GR	0	1
MOD_DCIB_FD	0	1
MOD_DCIB_TRVL	0	1
MOD_DCIB_FASHIOM	0	1
MOD_DCIB_Others	1	0
VALUE_DCIB_LT100	1	0
VALUE_DCIB_100_1K	1	0
VALUE_DCIB_1K_20K	0	1
VALUE_DCIB_GT20K	0	0

Iteration History^a

Iteration	Change in Cluster Centers	
	1	2
1	1.176	1.144
2	0.068	0.090
3	0.105	0.191
4	0.091	0.231
5	0.048	0.136

6	0.010	0.028
7	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 7. The minimum distance between initial centers is 3.000.

Final Cluster Centers

	Cluster	
	1	2
MOD_DCIB_ELEC	0	1
MOD_DCIB_GR	0	1
MOD_DCIB_FD	0	1
MOD_DCIB_TRVL	0	1
MOD_DCIB_FASHIOM	0	1
MOD_DCIB_Others	0	0
VALUE_DCIB_LT100	0	0
VALUE_DCIB_100_1K	0	0
VALUE_DCIB_1K_20K	0	0
VALUE_DCIB_GT20K	0	1

Number of Cases in each Cluster

Cluster	1	146.000
	2	55.000
Valid		201.000
Missing		0.000

For UPI: After the final clustering, all type of purchases, along with value of purchase between 1K & 20K is clustered together.

Table 15: K-Means Mod v/s Value for UPI

	Initial Cluster Centers	
	Cluster	
	1	2
MOD_UPI_ELEC	1	0
MOD_UPI_GR	1	0
MOD_UPI_FD	1	0
MOD_UPI_TRVL	1	0
MOD_UPI_FASHION	1	0
MOD_UPI_Others	0	1
VALUE_UPI_LT100	1	0
VALUE_UPI_100_1K	1	0
VALUE_UPI_1K_20K	1	1
VALUE_UPI_GT20K	1	0

Iteration	Iteration History ^a	
	Change in Cluster Centers	
	1	2
1	1.277	1.254
2	0.218	0.080
3	0.032	0.012
4	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 4. The minimum distance between initial centers is 3.000.

Final Cluster Centers

	Cluster	
	1	2
MOD_UPI_ELEC	1	0
MOD_UPI_GR	1	0
MOD_UPI_FD	1	0
MOD_UPI_TRVL	1	0
MOD_UPI_FASHION	1	0
MOD_UPI_Others	1	0
VALUE_UPI_LT100	0	0
VALUE_UPI_100_1K	0	0
VALUE_UPI_1K_20K	1	0
VALUE_UPI_GT20K	0	0

Number of Cases in each Cluster

Cluster	1	60.000
	2	141.000
Valid		201.000
Missing		0.000

For DW: After the final clustering, all type of purchases except for other were found to be part of cluster two for mode of payment as Digital wallet with no variables in cluster one.

Table 16:K-Means Mod v/s Value for DW

	Initial Cluster Centers	
	Cluster	
	1	2
MOD_DW_ELEC	0	0
MOD_DW_GR	1	0
MOD_DW_FD	0	1
MOD_DW_TRVL	0	1
MOD_DW_Fashion	0	1
MOD_DW_Others	0	0
VALUE_DW_LT100	0	1
VALUE_DW_100_1K	0	1
VALUE_DW_1K_20K	1	0
VALUE_DW_GT20K	0	0

Iteration	Iteration History ^a	
	Change in Cluster Centers	
	1	2
1	1.226	1.162
2	0.156	0.402
3	0.120	0.421
4	0.030	0.112
5	0.022	0.086
6	0.019	0.078
7	0.010	0.043

8	0.036	0.172
9	0.011	0.054
10	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 10. The minimum distance between initial centers is 2.646.

Final Cluster Centers

	Cluster	
	1	2
MOD_DW_ELEC	0	1
MOD_DW_GR	0	1
MOD_DW_FD	0	1
MOD_DW_TRVL	0	1
MOD_DW_Fashion	0	1
MOD_DW_Others	0	0
VALUE_DW_LT100	0	0
VALUE_DW_100_1K	0	0
VALUE_DW_1K_20K	0	0
VALUE_DW_GT20K	0	0

Number of Cases in each Cluster

Cluster	1	167.000
	2	34.000
Valid		201.000
Missing		0.000

For BNPL: There is only one cluster of significance obtained after final clustering with all type of payments except for others behaving as a cluster.

Table 17: K-Means Mod v/s Value for BNPL

Initial Cluster Centers

	Cluster	
	1	2
MOD_BNPL_ELEC	1	0
MOD_BNPL_GR	1	0
MOD_BNPL_FD	1	0
MOD_BNPL_TRVL	1	0
MOD_BNPL_Fashion	0	0
MOD_BNPL_Others	0	1
VALUE_BNPL_LT100	1	0
VALUE_BNPL_100_1K	1	0
VALUE_BNPL_1K_20K	1	0
VALUE_BNPL_GT20K	0	1

Iteration History^a

Iteration	Change in Cluster Centers	
	1	2
1	1.310	1.190
2	0.204	0.037
3	0.050	0.008
4	0.000	0.000

a. Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is .000. The current iteration is 4. The minimum distance between initial centers is 3.000.

Final Cluster Centers

	Cluster	
	1	2
MOD_BNPL_ELEC	1	0
MOD_BNPL_GR	1	0
MOD_BNPL_FD	1	0
MOD_BNPL_TRVL	1	0
MOD_BNPL_Fashion	1	0
MOD_BNPL_Others	0	0
VALUE_BNPL_LT100	0	0
VALUE_BNPL_100_1K	0	0
VALUE_BNPL_1K_20K	0	0
VALUE_BNPL_GT20K	0	0

Number of Cases in each Cluster

Cluster	1	30.000
	2	171.000
Valid		201.000
Missing		0.000

K-Mean clustering for each payment type was done to understand the clustering of different type and value of purchases for a specific payment type. Post various iterations, the final clustering indicated

that most variables for the same payment types are part of single cluster (with a value of 1), while other variables are not affecting the purchase propensity.

Following final clusters based on type of payment mode are obtained through this.

Table 18: Type of Purchase Significance

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
MOD_COD _ELEC	MOD_CC_ ELEC	MOD_DCIB _ELEC	MOD_UPI_ ELEC	MOD_D W_ELEC	MOD_BNP L_ELEC
MOD_COD _FD	MOD_CC_ GR	MOD_DCIB _GR	MOD_UPI_ GR	MOD_D W_GR	MOD_BNP L_GR
MOD_COD _Fashion	MOD_CC_ FD	MOD_DCIB _FD	MOD_UPI_ FD	MOD_D W_FD	MOD_BNP L_FD
VALUE_C OD_100_1K	MOD_CC_ TRVL	MOD_DCIB _TRVL	MOD_UPI_ TRVL	MOD_D W_TRVL	MOD_BNP L_TRVL
	MOD_CC_ FASHION	MOD_DCIB _FASHIOM	MOD_UPI_ FASHION	MOD_D W_Fashio n	MOD_BNP L_Fashion
	VALUE_C C_1K_20K	VALUE_DC IB_GT20K	MOD_UPI_ Others		
	VALUE_C C_GT20K		VALUE_U PI_1K_20K		

4.3.2. Hierarchical Clustering

Many scientists and researchers have raised the issue of validity of K-mean clustering for binary variable as there is a high probability of ties in result leading to inconsistent clustering. Instead, they

have suggested Hierarchical clustering for the Binary data and cross validation of the previous results ((IBM SPSS, n.d., Ordóñez, 2003).

The process implemented is Average linkage, Agglomeration schedule with Six fixed clusters for variables. The proximity matrix is created along with a Dendrogram and case wise distance matrix to validate the result. Based on the results, following six clusters are identified, which are further developed based on the proximity matrix distance from centroid.

Table 19: Clustering of Purchase types

Cluster 1		Cluster 2		Cluster 3	
Variables	rs	Variables	rs	Variables	rs
MOD_COD_ELEC	1	MOD_COD_Other	2	MOD_CC_ELEC	3
MOD_COD_GR	1	MOD_CC_Others	2	MOD_CC_GR	3
MOD_COD_FD	1	MOD_DCIB_Other	2	MOD_CC_FD	3
MOD_COD_TRVL	1	MOD_UPI_Others	2	MOD_CC_TRVL	3
MOD_COD_Fashion	1	MOD_DW_Others	2	MOD_CC_FASHI	3
MOD_DCIB_ELEC	1	MOD_BNPL_Other	2	VALUE_CC_GT2	3
MOD_DCIB_FD	1	VALUE_COD_LT	2	0K	
MOD_DCIB_TRV	1	VALUE_CC_LT10	2		
L		0			

MOD_DCIB_FAS HIOM	1	VALUE_DCIB_L T100	2	Variables	Clusters
MOD_UPI_ELEC	1	VALUE_UPI_LT1 00	2	MOD_DCIB_GR	4
MOD_UPI_TRVL	1	VALUE_DW_LT1 00	2	MOD_UPI_GR	4
MOD_UPI_FASHI ON	1	VALUE_BNPL_L T100	2	MOD_UPI_FD	4
MOD_DW_ELEC	1				
MOD_DW_GR	1				
MOD_DW_FD	1			Clusters	
				Variables	rs
MOD_DW_TRVL	1	VALUE_COD_10 0_1K	5	Clusters	
				Variables	rs
MOD_DW_Fashio n	1	VALUE_CC_100_ 1K	5	VALUE_CC_1K_2 0K	6
MOD_BNPL_ELE C	1	VALUE_DCIB_10 0_1K	5	VALUE_DCIB_1K _20K	6
MOD_BNPL_GR	1	VALUE_UPI_100 _1K	5	VALUE_UPI_1K_ 20K	6
MOD_BNPL_FD	1	VALUE_DW_100 _1K	5		
MOD_BNPL_TRV L	1	VALUE_BNPL_10 0_1K	5		

MOD_BNPL_Fashi on	1
VALUE_COD_1K _20K	1
VALUE_COD_GT 20K	1
VALUE_DCIB_GT 20K	1
VALUE_UPI_GT2 0K	1
VALUE_DW_1K_ 20K	1
VALUE_DW_GT2 0K	1
VALUE_BNPL_1 K_20K	1
VALUE_BNPL_G T20K	1

Based the distance from the centroid and Dendrogram, it is identified that purchase value plays a significant role for customers especially for transactions greater than 20K and mode of transaction as UPI, Digital Wallet, COD, Debit Cards / Internet Banking, and BNPL.

COD: The affinity is very strong for Digital Wallets and COD (D: 4.243) at this purchase level. COD transactions greater than 20k are also found to have strong linkage to travel related purchases. For all other purchase values and transaction type, the distances were found to be higher.

CC: Grocery & Food delivery purchases behave similarly (D: CC GRx FD 6.41), while fashion and travel have strong affinity (D: CC FashionxTravel 6.928). Value of purchase across spend band doesn't impact any type of purchase other than greater than 20K as can be seen by Dendrogram.

From the Dendrogram, it can be deduced that customer purchase intensity varies with different mode of payments. Additionally, for different type and value of purchases within given mode of payments, the impact varies.

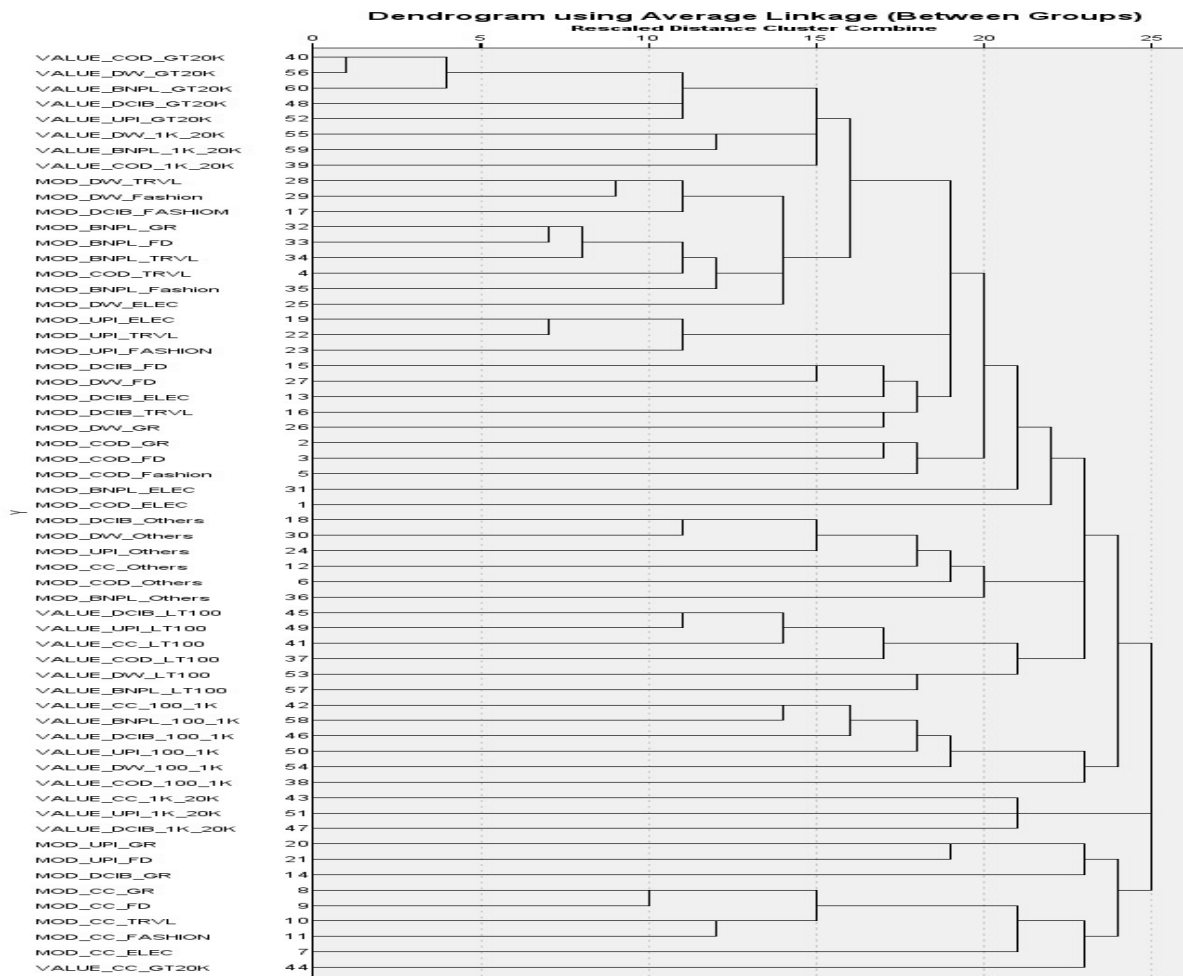


Figure 16: Dendrogram

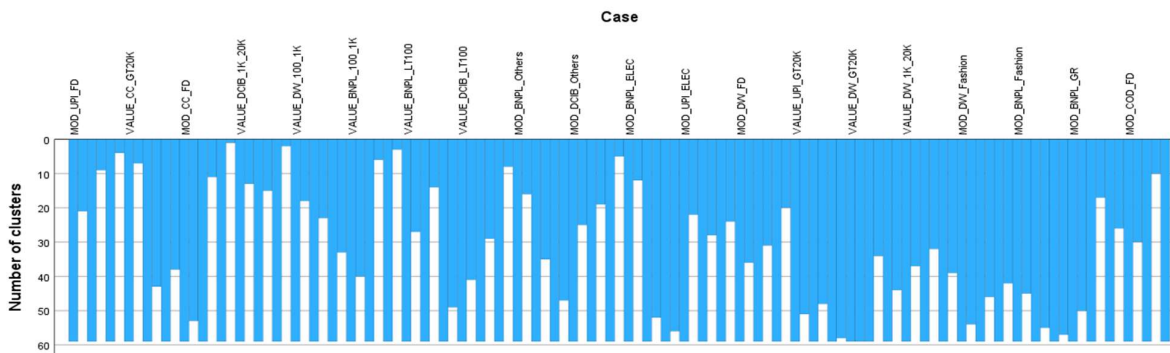


Figure 17: Case to Cluster mapping

The above deductions validate the earlier findings of K-mean Clustering. The author shall be using these clusters as constructs for PLS-SEM analysis.

Based on Hierarchical clustering, following insights have been identified:

1. For Credit Card purchases, customer behaviour for Food delivery and Grocery are similar, while transactions for travel and fashion share similar purchase pattern. Credit card purchase behaviour is significant for 20K and above transactions only. For smaller transactions impact of customer having a credit card is not significant.
2. Customers behave in a similar manner for transactions between Rs 100 to 1000 for all payment method with closest pattern seen for Credit card and BNPL.
3. Apart from credit card, customer purchase pattern for all other payment modes with transactions more than 20K is similar with closest proximity between COD & DW. These patterns are also similar to purchases between Rs 1000 to Rs 20K for COD, BNPL, and Digital Wallet.
4. Travel and Fashion transactions on Digital wallet follow similar pattern which also matches with the Fashion related purchases through Debit Card / Internet Banking.
5. For BNPL, Travel is closely related to Food delivery & Grocery purchases done through this mode.
6. For UPI payments, Food delivery and Grocery purchase patterns are very different from UPI based Travel, Fashion, and electronics purchases.

While a confirmatory analysis is being done through PLS-SEM, the above insights clearly indicate that type of payment method has significant impact of customer purchase pattern. Another important point highlighted here is the role of value, and type of purchase in determining purchase propensity of the customer.

4.3.3. PLS - SEM:

4.3.3.1. Model creation and loading the variables:

For the purpose of PLS SEM, as discussed earlier in the study, a total of 71 questions were asked from the participants of the survey which contained mix scale questions. Out of these survey questions, few of the multiple answer questions were converted to binary for the analysis which resulted in a total of 119 variables. Out of these 119 variables, 57 variables were retained for the PLS SEM out model creation.

List of retained indicators:

Construct	Indicator	Questions
AOT	1clickPayment	1click Payment affect the choice of payment method in E-commerce transactions
	High_security	Higher security needs affect the choice of payment method in E-commerce transactions
	Ease_payment	Ease of payments affect the choice of payment methods in E-commerce transactions
	Widespread_availability	Widespread availability of payment method affect the choice of payment method in E-commerce transactions
	UI_CX	UI_CX affect the choice of payment method in E-commerce transactions
	Merc_Acceptability	Acceptability of Payment method by merchant affect the choice of payment method in E-commerce transaction
Age	Age	Age affect the choice of payment method in E-commerce transactions

EE	EE2	Digital payment methods are easy to learn and use for online shopping
	EE3	One-click Payment has made my E-commerce purchases convenient and faster
EFC-1	Reviews	Reviews affect the choice of payment method in E-commerce transactions
	WOM	Word of Mouth affect the choice of payment method in E-commerce transactions
	Promo_Advert	Promotions & Advertisements affect the choice of payment method in E-commerce transactions
EFC-2	Govern_Policy	Govern_Policy affects the choice of payment method in E-commerce transactions
	Geopolitical	Word of Mouth affect the choice of payment method in E-commerce transactions
FC	FC1	My Knowledge of Digital Payments has helped me in using new E-commerce apps
	FC4	Digital payment authentication & security helps in reducing E-commerce risk of fraudulent transactions
Freq_BNPL	Freq_TOP6	Frequency of BNPL purchases for E-commerce in last 12 months
Freq_CC	Freq_TOP2	Frequency of CC purchases for E-commerce in last 12 months
Freq_COD	Freq_TOP1	Frequency of COD purchases for E-commerce in last 12 months

Freq_D CIB	Freq_TOP3	Frequency of DCIB purchases for E-commerce in last 12 months
Freq_D W	Freq_TOP5	Frequency of DW purchases for E-commerce in last 12 months
Freq_UP I	Freq_TOP4	Frequency of UPI purchases for E-commerce in last 12 months
Gender	Gender	Gender affects the choice of payment method in E-commerce transactions
HM	HM1	The fun of earning rewards points / discounts on payments makes the online shopping more exciting.
	HM2	I find shopping online using digital payment to be fun and Enjoyable
Income	Income	Income affects the choice of payment method in N-commerce transactions
MOD_B NPL_	MOD_BNPL _FD	I use BNPL for Food delivery payments
	MOD_BNPL _GR	I use BNPL for Grocery purchases
	MOD_BNPL _TRVL	I use BNPL for Travel related purchases
MOD_C C	MOD_CC_Fa shion	I use credit Card for Fashion related purchases
	MOD_CC_G R	I buy Grocery using credit card
	MOD_CC_T RVL	I use credit card for travel related transactions

	VALUE_CC_ GT20K	I use Credit Card for more than 20K purchases
MOD_D W_	MOD_DW_F ashion	I use Digital wallet for Fashion products purchases
MOD_U PI	MOD_UPI_F D	I use UPI for Food delivery payments
	MOD_UPI_G R	I use UPI for Grocery purchases
	MOD_UPI_F ashion	I use UPI for Fashion related purchases
PE	PE1	I find Digital payments convenient for tracking my E-commerce purchases
	PE3	I get more discounts and offers on E-commerce website using Digital Payment
Payment Preferen ce	PP1	I mostly use one specific Digital payment method for my online purchase
	PP2	I believe that not having a credit card limits online purchases capacity
	PP3	Having multiple payment options with good credit limit & EMI gives me confidence to purchase online
	PP4	I expect E-commerce site / App to have my preferred payment method
Pricing	Rewards	Rewards / Loyalty points affect choice of payment method in E-commerce transactions

	Discount	Discount schemes affect choice of payment method in E-commerce transactions
	Fees_charges	Fees & Charges affect the choice of payment method in E-commerce transactions
SBE	BI2	I will switch to a rival E-comm site /app if it offers me good discounts on Digital payment methods
	BI3	I will switch purchases from my regular website if it stops offering my preferred payment method
	BI5	I am likely to cancel the purchase at checkout if the payment method looks suspicious
	BI6	I will not buy from secured E-comm websites if it stops providing secure payment methods.
SI	SI1	My Friends / Family members are saving a lot of money by using Digital payments to make online purchase
	SI2	My Friends / Family Members think that I will save money & time by using Digital payments to make online purchase
Trust	T1	I am more likely to trust a new E-commerce website if it offers me my trusted payment options
	T2	It will decrease my trust in an E-commerce site if it asks me to pay through unknown payment method
VALUE _GT20	VALUE_DW _GT20K	I use Digital wallet for more than Rs 20K purchases
	VALUE_DCI B_GT20K	I use Debit Card / Internet Banking for more than Rs 20K purchases

VALUE_UPI	I use UPI for more than Rs 20K purchase
_GT20k	

Figure 18: List of Retainer Indicators

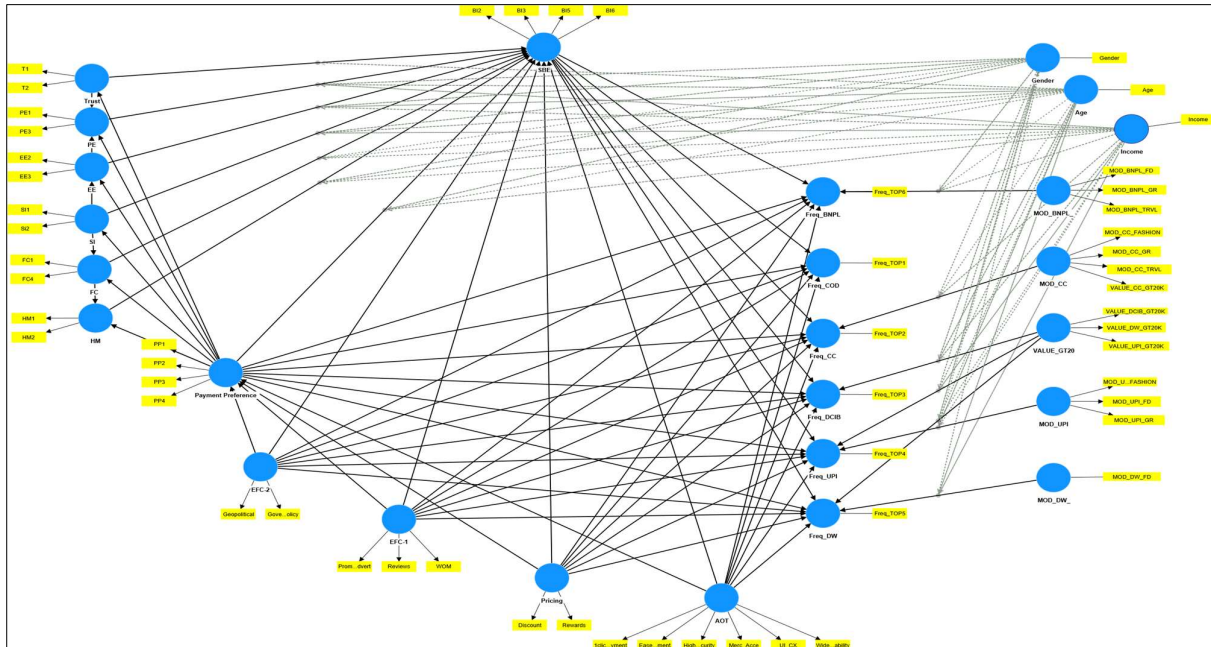


Figure 19: Updated Model Diagram

Outer Weight:

Table 20: Outer Weight

Indicator ← Construct	Outer Loading	Outer weights	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values
1clickPayment <- AOT	0.644	0.155	0.642	0.073	8.848	0.000
Age <- Age	1.000	1.000	1.000	0.000	n/a	n/a
BI2 <- SBE	0.805	0.365	0.804	0.030	26.688	0.000

						0
BI3 <- SBE	0.675	0.304	0.669	0.067	10.031	0.00 0
BI5 <- SBE	0.774	0.354	0.775	0.040	19.460	0.00 0
BI6 <- SBE	0.742	0.306	0.741	0.049	15.281	0.00 0
Discount <- Pricing	0.925	0.590	0.923	0.017	53.591	0.00 0
EE2 <- EE	0.831	0.515	0.827	0.041	20.483	0.00 0
EE3 <- EE	0.894	0.639	0.895	0.020	43.653	0.00 0
Ease_payment <- AOT	0.793	0.235	0.792	0.039	20.144	0.00 0
FC1 <- FC	0.855	0.585	0.851	0.034	24.934	0.00 0
FC4 <- FC	0.855	0.585	0.855	0.027	31.331	0.00 0
Freq_TOP1 <- Freq_COD	1.000	1.000	1.000	0.000	n/a	n/a
Freq_TOP2 <- Freq_CC	1.000	1.000	1.000	0.000	n/a	n/a
Freq_TOP3 <- Freq_DCIB	1.000	1.000	1.000	0.000	n/a	n/a
Freq_TOP4 <- Freq_UPI	1.000	1.000	1.000	0.000	n/a	n/a
Freq_TOP5 <- Freq_DW	1.000	1.000	1.000	0.000	n/a	n/a
Freq_TOP6 <-	1.000	1.000	1.000	0.000	n/a	n/a

Freq_BNPL						
Gender <- Gender	1.000	1.000	1.000	0.000	n/a	n/a
Geopolitical <- EFC-2	0.907	0.548	0.906	0.022	41.282	0.00 0
Govern_Policy <- EFC-2	0.909	0.553	0.908	0.024	37.873	0.00 0
HM1 <- HM	0.919	0.687	0.920	0.013	71.203	0.00 0
HM2 <- HM	0.806	0.457	0.803	0.047	17.006	0.00 0
High_security <- AOT	0.681	0.186	0.679	0.076	9.007	0.00 0
Income <- Income	1.000	1.000	1.000	0.000	n/a	n/a
MOD_BNPL_FD <- MOD_BNPL_	0.925	0.643	0.881	0.176	5.258	0.00 0
MOD_BNPL_GR <- MOD_BNPL_	0.809	0.417	0.761	0.166	4.887	0.00 0
MOD_BNPL_TRVL <- MOD_BNPL_	0.570	0.118	0.525	0.208	2.733	0.00 6
MOD_CC_FASHION <- MOD_CC	0.794	0.346	0.790	0.043	18.571	0.00 0
MOD_CC_GR <- MOD_CC	0.667	0.281	0.663	0.065	10.285	0.00 0
MOD_CC_TRVL <- MOD_CC	0.788	0.324	0.784	0.044	17.800	0.00 0

MOD_DW_FD <- MOD_DW_	1.000	1.000	1.000	0.000	n/a	n/a
MOD_UPI_FASHION <- MOD_UPI	0.681	0.352	0.672	0.108	6.290	0.00 0
MOD_UPI_FD <- MOD_UPI	0.734	0.383	0.716	0.095	7.698	0.00 0
MOD_UPI_GR <- MOD_UPI	0.853	0.562	0.846	0.055	15.438	0.00 0
Merc_Acce <- AOT	0.767	0.238	0.766	0.047	16.326	0.00 0
PE1 <- PE	0.887	0.567	0.886	0.023	38.590	0.00 0
PE3 <- PE	0.885	0.562	0.884	0.022	40.499	0.00 0
PP1 <- Payment Preference	0.616	0.269	0.610	0.081	7.647	0.00 0
PP2 <- Payment Preference	0.739	0.327	0.736	0.054	13.727	0.00 0
PP3 <- Payment Preference	0.778	0.429	0.778	0.040	19.633	0.00 0
PP4 <- Payment Preference	0.729	0.355	0.727	0.054	13.518	0.00 0
Promo_Advert <- EFC-1	0.776	0.431	0.769	0.064	12.168	0.00 0
Reviews <- EFC-1	0.738	0.365	0.730	0.071	10.394	0.00

						0
Rewards <- Pricing	0.897	0.506	0.895	0.030	29.713	0.00 0
SI1 <- SI	0.907	0.600	0.906	0.023	39.190	0.00 0
SI2 <- SI	0.875	0.521	0.874	0.027	32.188	0.00 0
T1 <- Trust	0.859	0.549	0.857	0.034	25.422	0.00 0
T2 <- Trust	0.883	0.598	0.883	0.025	36.009	0.00 0
UI_CX <- AOT	0.808	0.286	0.807	0.031	25.722	0.00 0
VALUE_CC_GT20K <- MOD_CC	0.674	0.419	0.674	0.058	11.671	0.00 0
VALUE_DCIB_GT20K <- VALUE_GT20	0.813	0.454	0.812	0.052	15.690	0.00 0
VALUE_DW_GT20K <- VALUE_GT20	0.723	0.372	0.708	0.083	8.730	0.00 0
VALUE_UPI_GT20K <- VALUE_GT20	0.823	0.434	0.820	0.051	16.186	0.00 0
WOM <- EFC-1	0.777	0.510	0.774	0.057	13.533	0.00 0
Widespread_availability <- AOT	0.801	0.216	0.800	0.035	22.714	0.00 0

Age x MOD_CC -> Age x MOD_CC	1.000	1.000	1.000	0.000	n/a	n/a
Age x Trust -> Age x Trust	1.000	1.000	1.000	0.000	n/a	n/a
Gender x MOD_BNPL_ - > Gender x MOD_BNPL_	1.000	1.000	1.000	0.000	n/a	n/a
Age x MOD_UPI -> Age x MOD_UPI	1.000	1.000	1.000	0.000	n/a	n/a
Age x VALUE_GT20 -> Age x VALUE_GT20	1.000	1.000	1.000	0.000	n/a	n/a
Income x EE -> Income x EE	1.000	1.000	1.000	0.000	n/a	n/a
Age x PE -> Age x PE	1.000	1.000	1.000	0.000	n/a	n/a
Age x FC -> Age x FC	1.000	1.000	1.000	0.000	n/a	n/a
Age x SI -> Age x SI	1.000	1.000	1.000	0.000	n/a	n/a
Income x MOD_DW_ -> Income x MOD_DW_	1.000	1.000	1.000	0.000	n/a	n/a
Age x HM -> Age x HM	1.000	1.000	1.000	0.000	n/a	n/a
Gender x EE -> Gender x EE	1.000	1.000	1.000	0.000	n/a	n/a
Income x VALUE_GT20 - > Income x VALUE_GT20	1.000	1.000	1.000	0.000	n/a	n/a
Income x PE -> Income x PE	1.000	1.000	1.000	0.000	n/a	n/a

Income x FC -> Income x FC	1.000	1.000	1.000	0.000	n/a	n/a
Age x MOD_DW_ -> Age x MOD_DW_	1.000	1.000	1.000	0.000	n/a	n/a
Income x MOD_BNPL_ - > Income x MOD_BNPL_	1.000	1.000	1.000	0.000	n/a	n/a
Income x MOD_UPI -> Income x MOD_UPI	1.000	1.000	1.000	0.000	n/a	n/a
Gender x MOD_CC -> Gender x MOD_CC	1.000	1.000	1.000	0.000	n/a	n/a
Gender x MOD_UPI -> Gender x MOD_UPI	1.000	1.000	1.000	0.000	n/a	n/a
Income x MOD_CC -> Income x MOD_CC	1.000	1.000	1.000	0.000	n/a	n/a
Age x MOD_BNPL_ -> Age x MOD_BNPL_	1.000	1.000	1.000	0.000	n/a	n/a
Gender x FC -> Gender x FC	1.000	1.000	1.000	0.000	n/a	n/a
Age x EE -> Age x EE	1.000	1.000	1.000	0.000	n/a	n/a
Gender x VALUE_GT20 - > Gender x VALUE_GT20	1.000	1.000	1.000	0.000	n/a	n/a
Gender x PE -> Gender x PE	1.000	1.000	1.000	0.000	n/a	n/a
Income x HM -> Income x	1.000	1.000	1.000	0.000	n/a	n/a

HM						
Gender x SI -> Gender x SI	1.000	1.000	1.000	0.000	n/a	n/a
Income x SI -> Income x SI	1.000	1.000	1.000	0.000	n/a	n/a
Gender x MOD_DW_ -> Gender x MOD_DW_	1.000	1.000	1.000	0.000	n/a	n/a
Gender x HM -> Gender x HM	1.000	1.000	1.000	0.000	n/a	n/a

4.3.3.2. Reliability & Validity

The construct reliability is measured through Cronbach's alpha & Composite Rho. As discussed earlier in the literature review, which values of 0.7 and above is considered highly reliable, values of 0.6 – 0.7 is also considered as adequate for reliability. Convergent validity is confirmed through a value of 0.5 & above for AVE.

Table 21: Reliability and Validity

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AOT	0.846	0.864	0.886	0.565
EE	0.661	0.682	0.854	0.745
EFC-1	0.648	0.655	0.808	0.583
EFC-2	0.788	0.788	0.904	0.825
FC	0.631	0.631	0.844	0.731
HM	0.674	0.750	0.855	0.747

MOD_BNPL				
–	0.728	0.899	0.820	0.612
MOD_CC	0.713	0.715	0.822	0.537
MOD_UPI	0.640	0.687	0.802	0.577
PE	0.725	0.725	0.879	0.785
Payment				
Preference	0.689	0.706	0.809	0.515
Pricing	0.796	0.810	0.907	0.830
SBE	0.740	0.747	0.837	0.563
SI	0.743	0.753	0.886	0.795
Trust	0.682	0.686	0.863	0.759
VALUE_GT				
20	0.707	0.710	0.830	0.621

4.3.3.3. Discriminant Validity:

This study uses HTMT test (Henseler et al., 2015) to validate the dissimilarity of constructs.

Additional validation is done through manual review of outer loadings to check for any outliers with relatively higher loading for other constructs than the parent one. None of the indicators had a value of more than 0.85, confirming discriminant validity in the model.

Table 22: HTMT

Indicator <- Construct	Heterotrait-monotrait ratio (HTMT)
Age <-> AOT	0.198
EE <-> AOT	0.663

EE <-> Age	0.373
EFC-1 <-> AOT	0.761
EFC-1 <-> Age	0.087
EFC-1 <-> EE	0.426
EFC-2 <-> AOT	0.652
EFC-2 <-> Age	0.101
EFC-2 <-> EE	0.534
EFC-2 <-> EFC-1	0.792
FC <-> AOT	0.591
FC <-> Age	0.327
FC <-> EE	0.899
FC <-> EFC-1	0.436
FC <-> EFC-2	0.436
Freq_BNPL <-> AOT	0.093
Freq_BNPL <-> Age	0.066
Freq_BNPL <-> EE	0.147
Freq_BNPL <-> EFC-1	0.213
Freq_BNPL <-> EFC-2	0.128
Freq_BNPL <-> FC	0.098
Freq_CC <-> AOT	0.196
Freq_CC <-> Age	0.303
Freq_CC <-> EE	0.261
Freq_CC <-> EFC-1	0.092
Freq_CC <-> EFC-2	0.066
Freq_CC <-> FC	0.269

Freq_CC <-> Freq_BNPL	0.050
Freq_COD <-> AOT	0.076
Freq_COD <-> Age	0.038
Freq_COD <-> EE	0.097
Freq_COD <-> EFC-1	0.152
Freq_COD <-> EFC-2	0.135
Freq_COD <-> FC	0.091
Freq_COD <-> Freq_BNPL	0.168
Freq_COD <-> Freq_CC	0.122
Freq_DCIB <-> AOT	0.100
Freq_DCIB <-> Age	0.004
Freq_DCIB <-> EE	0.031
Freq_DCIB <-> EFC-1	0.127
Freq_DCIB <-> EFC-2	0.063
Freq_DCIB <-> FC	0.047
Freq_DCIB <-> Freq_BNPL	0.143
Freq_DCIB <-> Freq_CC	0.292
Freq_DCIB <-> Freq_COD	0.264
Freq_DW <-> AOT	0.076
Freq_DW <-> Age	0.052
Freq_DW <-> EE	0.052
Freq_DW <-> EFC-1	0.132
Freq_DW <-> EFC-2	0.063
Freq_DW <-> FC	0.050
Freq_DW <-> Freq_BNPL	0.367

Freq_DW <-> Freq_CC	0.194
Freq_DW <-> Freq_COD	0.327
Freq_DW <-> Freq_DCIB	0.479
Freq_UPI <-> AOT	0.064
Freq_UPI <-> Age	0.040
Freq_UPI <-> EE	0.125
Freq_UPI <-> EFC-1	0.070
Freq_UPI <-> EFC-2	0.035
Freq_UPI <-> FC	0.143
Freq_UPI <-> Freq_BNPL	0.093
Freq_UPI <-> Freq_CC	0.224
Freq_UPI <-> Freq_COD	0.264
Freq_UPI <-> Freq_DCIB	0.447
Freq_UPI <-> Freq_DW	0.292
Gender <-> AOT	0.118
Gender <-> Age	0.216
Gender <-> EE	0.037
Gender <-> EFC-1	0.155
Gender <-> EFC-2	0.132
Gender <-> FC	0.064
Gender <-> Freq_BNPL	0.043
Gender <-> Freq_CC	0.177
Gender <-> Freq_COD	0.125
Gender <-> Freq_DCIB	0.082
Gender <-> Freq_DW	0.031

Gender <-> Freq_UPI	0.006
HM <-> AOT	0.512
HM <-> Age	0.288
HM <-> EE	0.857
HM <-> EFC-1	0.407
HM <-> EFC-2	0.544
HM <-> FC	0.725
HM <-> Freq_BNPL	0.078
HM <-> Freq_CC	0.369
HM <-> Freq_COD	0.095
HM <-> Freq_DCIB	0.041
HM <-> Freq_DW	0.036
HM <-> Freq_UPI	0.084
HM <-> Gender	0.101
Income <-> AOT	0.264
Income <-> Age	0.363
Income <-> EE	0.335
Income <-> EFC-1	0.100
Income <-> EFC-2	0.064
Income <-> FC	0.246
Income <-> Freq_BNPL	0.128
Income <-> Freq_CC	0.426
Income <-> Freq_COD	0.139
Income <-> Freq_DCIB	0.076
Income <-> Freq_DW	0.194

Income <-> Freq_UPI	0.144
Income <-> Gender	0.154
Income <-> HM	0.204
MOD_BNPL_ <-> AOT	0.114
MOD_BNPL_ <-> Age	0.079
MOD_BNPL_ <-> EE	0.123
MOD_BNPL_ <-> EFC-1	0.124
MOD_BNPL_ <-> EFC-2	0.116
MOD_BNPL_ <-> FC	0.092
MOD_BNPL_ <-> Freq_BNPL	0.168
MOD_BNPL_ <-> Freq_CC	0.054
MOD_BNPL_ <-> Freq_COD	0.064
MOD_BNPL_ <-> Freq_DCIB	0.113
MOD_BNPL_ <-> Freq_DW	0.148
MOD_BNPL_ <-> Freq_UPI	0.069
MOD_BNPL_ <-> Gender	0.069
MOD_BNPL_ <-> HM	0.110
MOD_BNPL_ <-> Income	0.125
MOD_CC <-> AOT	0.303
MOD_CC <-> Age	0.258
MOD_CC <-> EE	0.182
MOD_CC <-> EFC-1	0.116
MOD_CC <-> EFC-2	0.140
MOD_CC <-> FC	0.341
MOD_CC <-> Freq_BNPL	0.121

MOD_CC <-> Freq_CC	0.610
MOD_CC <-> Freq_COD	0.163
MOD_CC <-> Freq_DCIB	0.141
MOD_CC <-> Freq_DW	0.147
MOD_CC <-> Freq_UPI	0.149
MOD_CC <-> Gender	0.262
MOD_CC <-> HM	0.299
MOD_CC <-> Income	0.439
MOD_CC <-> MOD_BNPL_	0.290
MOD_DW_ <-> AOT	0.109
MOD_DW_ <-> Age	0.032
MOD_DW_ <-> EE	0.027
MOD_DW_ <-> EFC-1	0.042
MOD_DW_ <-> EFC-2	0.002
MOD_DW_ <-> FC	0.071
MOD_DW_ <-> Freq_BNPL	0.070
MOD_DW_ <-> Freq_CC	0.135
MOD_DW_ <-> Freq_COD	0.053
MOD_DW_ <-> Freq_DCIB	0.168
MOD_DW_ <-> Freq_DW	0.216
MOD_DW_ <-> Freq_UPI	0.044
MOD_DW_ <-> Gender	0.121
MOD_DW_ <-> HM	0.001
MOD_DW_ <-> Income	0.188
MOD_DW_ <-> MOD_BNPL_	0.369

MOD_DW_ <-> MOD_CC	0.413
MOD_UPI <-> AOT	0.143
MOD_UPI <-> Age	0.109
MOD_UPI <-> EE	0.127
MOD_UPI <-> EFC-1	0.122
MOD_UPI <-> EFC-2	0.093
MOD_UPI <-> FC	0.267
MOD_UPI <-> Freq_BNPL	0.056
MOD_UPI <-> Freq_CC	0.125
MOD_UPI <-> Freq_COD	0.078
MOD_UPI <-> Freq_DCIB	0.150
MOD_UPI <-> Freq_DW	0.081
MOD_UPI <-> Freq_UPI	0.321
MOD_UPI <-> Gender	0.202
MOD_UPI <-> HM	0.164
MOD_UPI <-> Income	0.209
MOD_UPI <-> MOD_BNPL_	0.486
MOD_UPI <-> MOD_CC	0.696
MOD_UPI <-> MOD_DW_	0.565
PE <-> AOT	0.550
PE <-> Age	0.271
PE <-> EE	0.893
PE <-> EFC-1	0.468
PE <-> EFC-2	0.464
PE <-> FC	0.803

PE <-> Freq_BNPL	0.030
PE <-> Freq_CC	0.332
PE <-> Freq_COD	0.020
PE <-> Freq_DCIB	0.058
PE <-> Freq_DW	0.023
PE <-> Freq_UPI	0.088
PE <-> Gender	0.047
PE <-> HM	0.878
PE <-> Income	0.235
PE <-> MOD_BNPL_	0.090
PE <-> MOD_CC	0.302
PE <-> MOD_DW_	0.075
PE <-> MOD_UPI	0.110
Payment Preference <-> AOT	0.578
Payment Preference <-> Age	0.263
Payment Preference <-> EE	0.844
Payment Preference <-> EFC-1	0.583
Payment Preference <-> EFC-2	0.632
Payment Preference <-> FC	0.769
Payment Preference <-> Freq_BNPL	0.044
Payment Preference <-> Freq_CC	0.339
Payment Preference <-> Freq_COD	0.108
Payment Preference <-> Freq_DCIB	0.097
Payment Preference <-> Freq_DW	0.063
Payment Preference <-> Freq_UPI	0.103

Payment Preference <-> Gender	0.176
Payment Preference <-> HM	0.899
Payment Preference <-> Income	0.212
Payment Preference <-> MOD_BNPL_	0.191
Payment Preference <-> MOD_CC	0.181
Payment Preference <-> MOD_DW_	0.078
Payment Preference <-> MOD_UPI	0.167
Payment Preference <-> PE	0.807
Pricing <-> AOT	0.691
Pricing <-> Age	0.230
Pricing <-> EE	0.352
Pricing <-> EFC-1	0.579
Pricing <-> EFC-2	0.413
Pricing <-> FC	0.420
Pricing <-> Freq_BNPL	0.016
Pricing <-> Freq_CC	0.254
Pricing <-> Freq_COD	0.030
Pricing <-> Freq_DCIB	0.067
Pricing <-> Freq_DW	0.126
Pricing <-> Freq_UPI	0.037
Pricing <-> Gender	0.301
Pricing <-> HM	0.474
Pricing <-> Income	0.262
Pricing <-> MOD_BNPL_	0.085
Pricing <-> MOD_CC	0.328

Pricing <-> MOD_DW_	0.076
Pricing <-> MOD_UPI	0.113
Pricing <-> PE	0.425
Pricing <-> Payment Preference	0.484
SBE <-> AOT	0.516
SBE <-> Age	0.358
SBE <-> EE	0.866
SBE <-> EFC-1	0.375
SBE <-> EFC-2	0.385
SBE <-> FC	0.879
SBE <-> Freq_BNPL	0.121
SBE <-> Freq_CC	0.338
SBE <-> Freq_COD	0.069
SBE <-> Freq_DCIB	0.047
SBE <-> Freq_DW	0.081
SBE <-> Freq_UPI	0.108
SBE <-> Gender	0.136
SBE <-> HM	0.812
SBE <-> Income	0.275
SBE <-> MOD_BNPL_	0.080
SBE <-> MOD_CC	0.243
SBE <-> MOD_DW_	0.140
SBE <-> MOD_UPI	0.177
SBE <-> PE	0.900
SBE <-> Payment Preference	0.864

SBE <-> Pricing	0.586
SI <-> AOT	0.477
SI <-> Age	0.235
SI <-> EE	0.657
SI <-> EFC-1	0.528
SI <-> EFC-2	0.516
SI <-> FC	0.615
SI <-> Freq_BNPL	0.088
SI <-> Freq_CC	0.172
SI <-> Freq_COD	0.068
SI <-> Freq_DCIB	0.033
SI <-> Freq_DW	0.019
SI <-> Freq_UPI	0.025
SI <-> Gender	0.087
SI <-> HM	0.673
SI <-> Income	0.076
SI <-> MOD_BNPL_	0.109
SI <-> MOD_CC	0.183
SI <-> MOD_DW_	0.129
SI <-> MOD_UPI	0.123
SI <-> PE	0.853
SI <-> Payment Preference	0.764
SI <-> Pricing	0.327
SI <-> SBE	0.611
Trust <-> AOT	0.487

Trust <-> Age	0.234
Trust <-> EE	0.651
Trust <-> EFC-1	0.363
Trust <-> EFC-2	0.434
Trust <-> FC	0.787
Trust <-> Freq_BNPL	0.081
Trust <-> Freq_CC	0.133
Trust <-> Freq_COD	0.094
Trust <-> Freq_DCIB	0.065
Trust <-> Freq_DW	0.030
Trust <-> Freq_UPI	0.076
Trust <-> Gender	0.166
Trust <-> HM	0.562
Trust <-> Income	0.231
Trust <-> MOD_BNPL_	0.067
Trust <-> MOD_CC	0.223
Trust <-> MOD_DW_	0.081
Trust <-> MOD_UPI	0.173
Trust <-> PE	0.716
Trust <-> Payment Preference	0.662
Trust <-> Pricing	0.448
Trust <-> SBE	0.895
Trust <-> SI	0.687
VALUE_GT20 <-> AOT	0.203
VALUE_GT20 <-> Age	0.089

VALUE_GT20 <-> EE	0.107
VALUE_GT20 <-> EFC-1	0.266
VALUE_GT20 <-> EFC-2	0.178
VALUE_GT20 <-> FC	0.126
VALUE_GT20 <-> Freq_BNPL	0.058
VALUE_GT20 <-> Freq_CC	0.183
VALUE_GT20 <-> Freq_COD	0.179
VALUE_GT20 <-> Freq_DCIB	0.397
VALUE_GT20 <-> Freq_DW	0.391
VALUE_GT20 <-> Freq_UPI	0.253
VALUE_GT20 <-> Gender	0.178
VALUE_GT20 <-> HM	0.121
VALUE_GT20 <-> Income	0.078
VALUE_GT20 <-> MOD_BNPL_	0.288
VALUE_GT20 <-> MOD_CC	0.386
VALUE_GT20 <-> MOD_DW_	0.429
VALUE_GT20 <-> MOD_UPI	0.468
VALUE_GT20 <-> PE	0.072
VALUE_GT20 <-> Payment Preference	0.121
VALUE_GT20 <-> Pricing	0.142
VALUE_GT20 <-> SBE	0.106
VALUE_GT20 <-> SI	0.091
VALUE_GT20 <-> Trust	0.088

The model is also tested for multi collinearity through VIF and while there are no formative constructs in the model, a model fit test was also conducted.

Table 23: Model FIT

	Saturated model	Estimated model
SRMR	0.064	0.097
d_ ULS	6.625	15.058
d_ G	2.569	3.828
Chi-square	2846.790	5130.253
NFI	0.525	0.143

BIC:

Table 24: BIC

Construct	BIC (Bayesian information criterion)
EE	-76.170
FC	-53.215
Freq_ BNPL	44.588
Freq_ CC	-27.610
Freq_ COD	30.019
Freq_ DCIB	38.755
Freq_ DW	47.774
Freq_ UPI	66.795
HM	-106.178
PE	-121.225
Payment Preference	-44.303
SBE	-87.345

SI	-64.420
Trust	-39.744

4.3.4. Significance Test

Tested the significance of the inner model through Bootstrapping (Hair et al., 2017) using the following bootstrap setting:

Table 25: Bootstrapping

Bootstrap	Setting
Complexity	Complete (slower)
Confidence interval method	Percentile bootstrap
Generate results per sample	No
Parallel processing	Yes
Samples	5000
Seed	Fixed seed
Significance level	0.1
Test type	Two tailed

Based on the bootstrapping, it can be sufficiently concluded that all the indicators are significant and have relevant loadings.

4.4. Assessing the Structural Model

4.4.1. VIF (Collinearity check)

The collinearity check has been done and data sample is found to be completely free from collinearity issue for outer model and minimal indirect impact on inner model.

Table 26: VIF

Outer Model	VIF	Inner model	VIF
1clickPayment	1.498	AOT -> Freq_BNPL	2.180
Age	1.000	AOT -> Freq_CC	2.239
BI2	1.559	AOT -> Freq_COD	2.062
BI3	1.268	AOT -> Freq_DCIB	2.258
BI5	1.487	AOT -> Freq_DW	2.276
BI6	1.426	AOT -> Freq_UPI	2.358
Discount	1.779	AOT -> Payment Preference	1.990
EE2	1.323	AOT -> SBE	2.817
EE3	1.323	Age -> Freq_BNPL	1.766
Ease_payment	1.872	Age -> Freq_CC	2.350
FC1	1.270	Age -> Freq_DCIB	1.583
FC4	1.270	Age -> Freq_DW	1.724
Freq_TOP1	1.000	Age -> Freq_UPI	3.597
Freq_TOP2	1.000	Age -> SBE	1.557
Freq_TOP3	1.000	EE -> PE	1.593
Freq_TOP4	1.000	EE -> SBE	3.383
Freq_TOP5	1.000	EFC-1 -> Freq_BNPL	1.867

Freq_TOP6	1.000
Gender	1.000
Geopolitical	1.731
Govern_Policy	1.731
HM1	1.348
HM2	1.348
High_security	1.492
Income	1.000
MOD_BNPL_FD	1.517
MOD_BNPL_GR	1.514
MOD_BNPL_TRVL	1.334
MOD_CC_FASHION	1.645
MOD_CC_GR	1.421
MOD_CC_TRVL	1.599
MOD_DW_FD	1.000
MOD_UPI_FASHION	1.208
MOD_UPI_FD	1.269
MOD_UPI_GR	1.305
Merc_Acce	1.821
PE1	1.479
PE3	1.479
PP1	1.241
PP2	1.397
PP3	1.349
PP4	1.304

EFC-1 -> Freq_CC	1.874
EFC-1 -> Freq_COD	1.803
EFC-1 -> Freq_DCIB	1.889
EFC-1 -> Freq_DW	1.949
EFC-1 -> Freq_UPI	1.940
EFC-1 -> Payment Preference	1.776
EFC-1 -> SBE	2.128
EFC-2 -> Freq_BNPL	1.798
EFC-2 -> Freq_CC	1.792
EFC-2 -> Freq_COD	1.768
EFC-2 -> Freq_DCIB	1.852
EFC-2 -> Freq_DW	1.878
EFC-2 -> Freq_UPI	1.875
EFC-2 -> Payment Preference	1.659
EFC-2 -> SBE	2.142
FC -> HM	1.346
FC -> SBE	2.800
Gender -> Freq_BNPL	1.498
Gender -> Freq_CC	2.473
Gender -> Freq_DCIB	1.444
Gender -> Freq_DW	1.614
Gender -> Freq_UPI	2.790
Gender -> SBE	1.301
HM -> SBE	2.947
Income -> Freq_BNPL	1.612

Promo_Advert	1.351	Income -> Freq_CC	2.975
Reviews	1.345	Income -> Freq_DCIB	1.615
Rewards	1.779	Income -> Freq_DW	1.829
SI1	1.537	Income -> Freq_UPI	3.598
Si2	1.537	Income -> SBE	1.568
T1	1.366	MOD_BNPL_ -> Freq_BNPL	1.106
T2	1.366	MOD_CC -> Freq_CC	1.373
UI_CX	1.833	MOD_DW_ -> Freq_DW	1.259
VALUE_CC_GT20K	1.166	MOD_UPI -> Freq_UPI	1.269
VALUE_DCIB_GT20K	1.278	PE -> SBE	3.527
VALUE_DW_GT20K	1.465	Payment Preference -> EE	1.445
VALUE_UPI_GT20K	1.469	Payment Preference -> FC	1.445
WOM	1.180	Payment Preference -> Freq_BNPL	2.016
Widespread_availability	2.040	Payment Preference -> Freq_CC	1.995
Income x VALUE_GT20	1.000	Payment Preference -> Freq_COD	1.966
Age x MOD_BNPL_	1.000	Payment Preference -> Freq_DCIB	1.992
Gender x FC	1.000	Payment Preference -> Freq_DW	2.009
Income x SI	1.000	Payment Preference -> Freq_UPI	2.051
Gender x SI	1.000	Payment Preference -> HM	1.346

Income x HM	1.000	Payment Preference -> PE	1.639
Income x MOD_UPI	1.000	Payment Preference -> SBE	2.599
Gender x MOD_CC	1.000	Payment Preference -> SI	1.000
Age x SI	1.000	Payment Preference -> Trust	1.000
Age x HM	1.000	Pricing -> Freq_BNPL	1.784
Age x EE	1.000	Pricing -> Freq_CC	1.774
Income x FC	1.000	Pricing -> Freq_COD	1.633
Age x MOD_UPI	1.000	Pricing -> Freq_DCIB	1.835
Gender x VALUE_GT20	1.000	Pricing -> Freq_DW	1.872
Income x MOD_BNPL_	1.000	Pricing -> Freq_UPI	1.962
Age x FC	1.000	Pricing -> Payment Preference	1.496
Gender x Payment Preference	1.000	Pricing -> SBE	2.048
Income x EE	1.000	SBE -> Freq_BNPL	1.955
Income x Payment Preference	1.000	SBE -> Freq_CC	1.942
Gender x MOD_DW_	1.000	SBE -> Freq_COD	1.851
Gender x PE	1.000	SBE -> Freq_DCIB	1.947
Age x Trust	1.000	SBE -> Freq_DW	1.959
Gender x MOD_BNPL_	1.000	SBE -> Freq_UPI	1.950
Gender x HM	1.000	SI -> EE	1.445
Age x PE	1.000	SI -> FC	1.445
Income x MOD_CC	1.000	SI -> SBE	2.446

Age x Payment Preference	1.000
Income x PE	1.000
Age x VALUE_GT20	1.000
Income x MOD_DW_	1.000
Age x MOD_DW_	1.000
Gender x MOD_UPI	1.000
Age x MOD_CC	1.000
Gender x EE	1.000

Trust -> PE	1.355
Trust -> SBE	2.339
VALUE_GT20 -> Freq_DCIB	1.422
VALUE_GT20 -> Freq_DW	1.630
VALUE_GT20 -> Freq_UPI	1.572
Gender x HM -> SBE	4.252
Gender x PE -> SBE	4.313
Age x VALUE_GT20 -> Freq_DCIB	1.493
Age x VALUE_GT20 -> Freq_DW	2.205
Age x VALUE_GT20 -> Freq_UPI	1.785
Income x SI -> SBE	2.732
Gender x MOD_CC -> Freq_CC	2.733
Gender x EE -> SBE	2.553
Income x VALUE_GT20 -> Freq_DCIB	1.690
Income x VALUE_GT20 -> Freq_DW	2.042
Income x VALUE_GT20 -> Freq_UPI	1.948
Income x HM -> SBE	4.513

Gender x SI -> SBE	2.986
Age x MOD_CC -> Freq_CC	2.575
Gender x MOD_DW_ -> Freq_DW	1.947
Age x SI -> SBE	3.135
Age x Trust -> SBE	2.233
Income x MOD_BNPL_ -> Freq_BNPL	1.734
Age x PE -> SBE	4.463
Gender x VALUE_GT20 -> Freq_DCIB	1.912
Gender x VALUE_GT20 -> Freq_DW	2.167
Gender x VALUE_GT20 -> Freq_UPI	2.114
Income x PE -> SBE	4.456
Age x MOD_DW_ -> Freq_DW	2.521
Income x FC -> SBE	2.977
Income x EE -> SBE	5.838
Gender x MOD_UPI -> Freq_UPI	3.010
Income x MOD_UPI -> Freq_UPI	3.776

Gender x MOD_BNPL_ -> Freq_BNPL	1.678
Age x FC -> SBE	3.165
Age x MOD_BNPL_ -> Freq_BNPL	1.494
Income x MOD_CC -> Freq_CC	3.203
Gender x FC -> SBE	2.512
Age x EE -> SBE	5.285
Age x MOD_UPI -> Freq_UPI	3.827
Age x HM -> SBE	6.977
Income x MOD_DW_ -> Freq_DW	2.045
Gender x Payment Preference - > SBE	2.972
Age x Payment Preference -> SBE	5.282
Income x Payment Preference - > SBE	3.732

4.4.2. R-Square:

The value of all the construct were checked and all variables except Freq_COD were found to significant and is explained by the model.

Table 27: R-Square

Construct	R2 - Original	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
EE	0.364	0.374	0.058	6.260	0.000
FC	0.287	0.298	0.062	4.664	0.000
Freq_BNPL	0.133	0.189	0.042	3.131	0.002
Freq_CC	0.395	0.435	0.048	8.201	0.000
Freq_COD	0.030	0.062	0.033	0.919	0.358
Freq_DCIB	0.158	0.217	0.049	3.186	0.001
Freq_DW	0.207	0.275	0.050	4.113	0.000
Freq_UPI	0.129	0.207	0.046	2.781	0.005
HM	0.453	0.463	0.059	7.686	0.000
PE	0.505	0.518	0.061	8.295	0.000
Payment Preference	0.293	0.324	0.056	5.216	0.000
SBE	0.732	0.783	0.033	22.253	0.000
SI	0.308	0.314	0.049	6.311	0.000
Trust	0.218	0.230	0.064	3.409	0.001

With a value of 0.732, the variance in SBE is well explained by the constructs. This is a strong corroboration for the model created. All other variables are also having significant values.

4.4.3. PLSpredict:

To corroborate the above findings and before actually discussing the Path co-efficient values, lets understand the predictability of the model using the PLSpredict (Shmueli et al., 2016, Sharma et al., 2019) for manifested variable (MV) and latent variable (LV).

Table 28 PLSPredict

MV	Q ² predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
EE2	0.114	1.031	0.732	1.158	0.820
EE3	0.152	1.231	0.902	1.210	0.895
FC1	0.130	1.194	0.870	1.283	0.965
FC4	0.077	1.195	0.886	1.235	0.951
Freq_TOP6	0.010	0.640	0.518	0.704	0.540
Freq_TOP2	0.033	0.759	0.586	0.670	0.542
Freq_TOP1	-0.027	0.692	0.531	0.711	0.564
Freq_TOP3	-0.024	0.719	0.540	0.729	0.578
Freq_TOP5	0.004	0.710	0.574	0.716	0.574
Freq_TOP4	-0.189	0.694	0.516	0.675	0.531
HM1	0.167	1.209	0.895	1.245	0.929
HM2	0.107	1.187	0.890	1.335	0.974
PE1	0.139	1.194	0.908	1.239	0.923
PE3	0.124	1.092	0.818	1.234	0.921
PP1	0.106	1.341	1.026	1.414	1.072
PP2	0.111	1.578	1.242	1.694	1.366
PP3	0.143	1.284	0.980	1.444	1.080
PP4	0.115	1.281	0.934	1.424	1.031
BI2	0.073	1.192	0.877	1.294	0.984
BI3	0.114	1.295	1.037	1.408	1.098
BI5	0.106	1.252	0.993	1.287	0.986
BI6	0.052	1.539	1.225	1.699	1.310
SI1	0.119	1.225	0.977	1.304	0.998

Si2	0.136	1.129	0.900	1.224	0.927
T1	0.085	1.511	1.161	1.656	1.270
T2	0.101	1.403	1.077	1.520	1.146

Based on the Q^2 value, it can be deduced that other than frequency of purchase for COD, Debit card / Internet Banking & UPI, the model is able to show robust predictability for all other indicators. This is also checked for latent variables which confirms the same for the model.

Table 29: Q2 Predict

Latent Variable	Q^2 predict	RMSE	MAE
EE	0.180	0.926	0.665
FC	0.142	0.944	0.676
Freq_BNPL	0.013	1.007	0.813
Freq_CC	0.035	0.991	0.764
Freq_COD	-0.027	1.022	0.783
Freq_DCIB	-0.024	1.021	0.767
Freq_DW	0.006	1.005	0.811
Freq_UPI	-0.190	1.103	0.817
HM	0.185	0.919	0.688
PE	0.168	0.924	0.703
Payment Preference	0.231	0.891	0.673
SBE	0.157	0.937	0.693
SI	0.160	0.927	0.714
Trust	0.122	0.953	0.724

4.4.4. Path Coefficient:

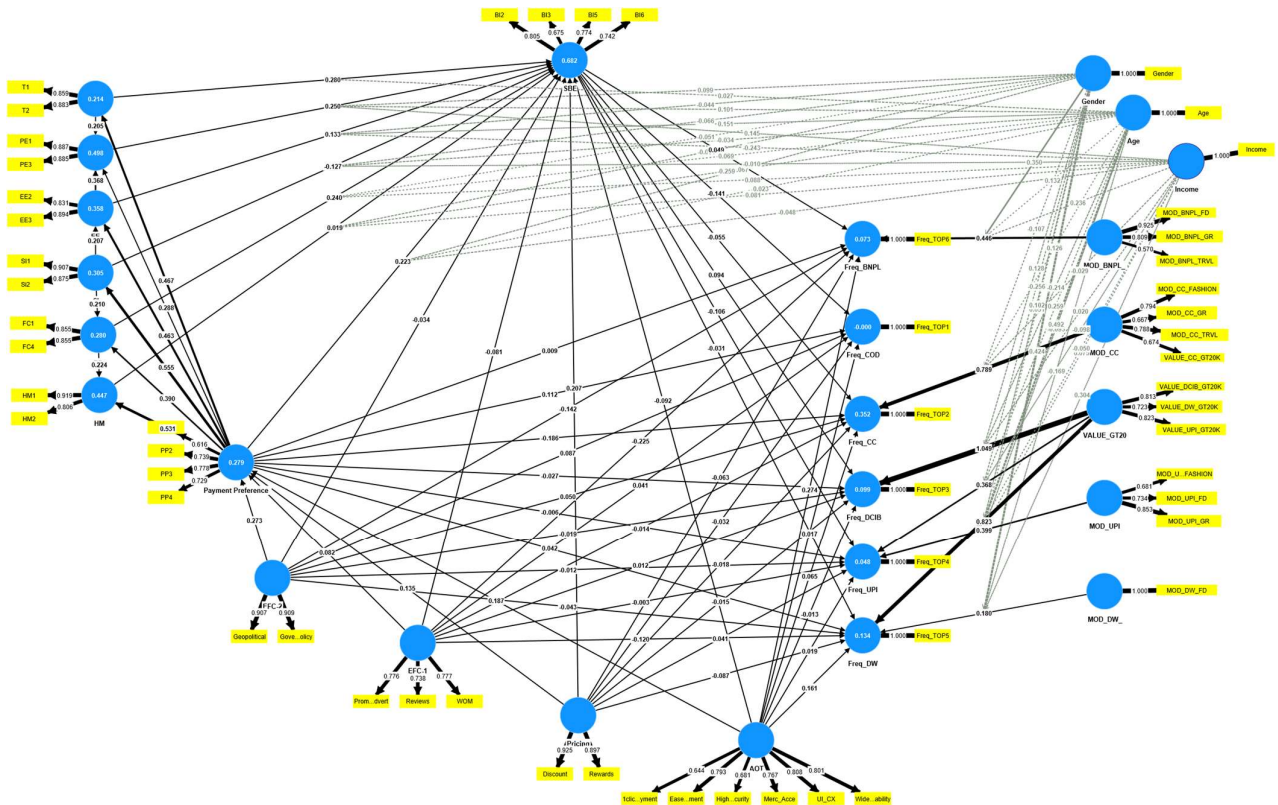


Figure 20: Path Coefficient

Based on the above details, for Path-coefficient value of more than 0.1 (+/-) and the required P value, we have 34 relationships which are significant relationships wherein the SD of dependent construct is affected by the SD of the construct.

Table 30: Inner Model Path Coefficient

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AOT -> Freq_BNPL	0.274	0.28	0.098	2.78	0.005

AOT -> Payment Preference	0.187	0.189	0.109	1.717	0.086
EE -> PE	0.368	0.371	0.07	5.236	0
EFC-1 -> Freq_BNPL	-0.225	-0.233	0.073	3.095	0.002
EFC-2 -> Freq_BNPL	-0.142	-0.139	0.075	1.9	0.057
EFC-2 -> Payment Preference	0.273	0.255	0.098	2.793	0.005
FC -> HM	0.224	0.226	0.059	3.787	0
FC -> SBE	0.231	0.221	0.077	2.981	0.003
Gender -> Freq_DCIB	0.137	0.134	0.074	1.857	0.063
Income -> Freq_CC	0.211	0.205	0.105	2.004	0.045
MOD_BNPL_ -> Freq_BNPL	0.446	0.481	0.239	1.864	0.062
MOD_CC -> Freq_CC	0.789	0.801	0.129	6.132	0
MOD_UPI -> Freq_UPI	0.399	0.422	0.152	2.635	0.008
PE -> SBE	0.25	0.239	0.093	2.697	0.007
Payment Preference -> EE	0.463	0.466	0.074	6.29	0
Payment Preference -> FC	0.39	0.393	0.083	4.692	0
Payment Preference -> Freq_CC	-0.186	-0.18	0.085	2.181	0.029
Payment Preference -> HM	0.531	0.533	0.06	8.885	0
Payment Preference -> PE	0.288	0.288	0.073	3.967	0
Payment Preference -> SBE	0.222	0.207	0.086	2.584	0.01
Payment Preference -> SI	0.555	0.559	0.044	12.627	0
Payment Preference -> Trust	0.467	0.474	0.068	6.842	0
Pricing -> SBE	0.207	0.188	0.076	2.717	0.007
SI -> EE	0.207	0.208	0.068	3.07	0.002

SI -> FC	0.21	0.209	0.074	2.848	0.004
SI -> SBE	-0.131	-0.113	0.075	1.742	0.082
Trust -> PE	0.205	0.202	0.077	2.673	0.008
Trust -> SBE	0.293	0.268	0.071	4.13	0
VALUE_GT20 -> Freq_DW	0.823	0.828	0.258	3.19	0.001
Age x VALUE_GT20 -> Freq_DW	0.492	0.45	0.296	1.662	0.097
Gender x MOD_DW_ -> Freq_DW	0.424	0.432	0.185	2.299	0.022
Income x EE -> SBE	-0.266	-0.238	0.123	2.162	0.031
Age x HM -> SBE	-0.246	-0.249	0.106	2.329	0.02
Income x MOD_DW_ -> Freq_DW	0.304	0.311	0.182	1.669	0.095

4.5. Hypothesis validation

This confirmatory study indicates the following hypothesis as validated:

Table 31: Inner Model Path Coefficient II

Inner Model	Path Co- efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
EE -> PE	0.368	0.371	0.07	5.236	0
EE -> SBE	0.129	0.112	0.096	1.35	0.177
FC -> HM	0.224	0.226	0.059	3.787	0
FC -> SBE	0.231	0.221	0.077	2.981	0.003
HM -> SBE	0.03	0.055	0.094	0.317	0.752

PE -> SBE	0.25	0.239	0.093	2.697	0.007
SI -> EE	0.207	0.208	0.068	3.07	0.002
SI -> FC	0.21	0.209	0.074	2.848	0.004
SI -> SBE	-0.131	-0.113	0.075	1.742	0.082
Trust -> PE	0.205	0.202	0.077	2.673	0.008
Trust -> SBE	0.293	0.268	0.071	4.13	0

H1: Performance expectancy for the payment method has a strong impact on the purchase intention (SBE) of the customer. This is validated as Path coefficient (PC) is 0.25 at a p value of 0.007 and confirms the statement that customers find convenience and discounts as a major driver for adoption of digital payment methods for online purchase intentions.

H2/H2A: Effort expectancy for the payment method has a strong impact on the performance expectancy of the payment method with 0.368 as PC. At the same time, EE mildly affects the customer purchase intention through digital payment mode at 0.129. This explains that ease of learning to pay through digital payment modes and service benefits of one click payment positively affect customer purchase intention through digital payment. While the P value is slightly higher for this construct but the PLSpredict confirms the validity of construct through Q2 of 0.180. Thus, both the hypothesis stands validated.

H3: With a PC of -0.131, social influence (SI) has a significant but negative impact on E-commerce service benefit expectation for purchases through digital payment mode wherein conformation & views from those consider important to customer will moderate the service benefit expectations of customer using digital payment mode.

H3A: Social Influence has a significant impact on Effort expectancy as indicated by a PC value of 0.207 at a significant P value of 0.002. This suggest that payment method views of significant others positively affect the customer views on ease of learning the payment method and that of one click payment.

H3B: Social Influence significantly impact the Facilitating condition as validated with a PC score of 0.21 at a p value of 0.004. This signifies that societal norm drives the customer understanding of payment method as well as positively affect their views of risk and frauds associated with the payment method.

H4: Facilitating Condition has a significant impact on E-commerce service benefit expectation through digital payment mode which is confirmed through a PC score of 0.231 at a p value of 0.004. This suggest that knowledge of payment method and security and risk mitigation helps in promoting customer behaviour toward digital payment method.

H4A: Facilitating Condition has a significant impact on Hedonic motivation as verified through a PC score of 0.224 which suggest that customer knowledge of payment method and associated risk aversion measures increase customers sense of delight while using digital payment method.

H5: HM doesn't have significant impact on customer's digital payment behaviour intentions for E-commerce purchases through digital payment method which rejects our null hypothesis.

H6: Trust has a significant impact on E-commerce SBE for digital payment methods as confirmed through the PC score of 0.293 which signifies that present of customer's trusted payment method increases customer's online purchase intention through digital payment mode and vice-versa.

H6A: Trust has a significant positive impact on Performance Expectancy as indicated through a PC score of 0.205. This explains that the presence of trusted payment method increases convenience of payment as well as customer perception of getting better discounts through the payment method.

Table 32: Inner Model Path Coefficient III

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Payment Preference -> EE	0.463	0.466	0.074	6.29	0
Payment Preference -> FC	0.39	0.393	0.083	4.692	0
Payment Preference -> Freq_BNPL	0.009	0.016	0.105	0.088	0.93
Payment Preference -> Freq_CC	-0.186	-0.18	0.085	2.181	0.029
Payment Preference -> Freq_COD	0.112	0.111	0.101	1.11	0.267
Payment Preference -> Freq_DCIB	-0.027	-0.031	0.101	0.272	0.786
Payment Preference -> Freq_DW	0.042	0.033	0.098	0.424	0.671
Payment Preference -> Freq_UPI	-0.006	-0.006	0.104	0.058	0.954
Payment Preference -> HM	0.531	0.533	0.06	8.885	0
Payment Preference -> PE	0.288	0.288	0.073	3.967	0
Payment Preference -> SBE	0.222	0.207	0.086	2.584	0.01
Payment Preference -> SI	0.555	0.559	0.044	12.627	0

Payment Preference -> Trust	0.467	0.474	0.068	6.842	0
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H7: Payment preference is a construct introduced in the model to explain the customer preference for the specific payment mode. It has four indicators specifying that while customer want multiple payment modes available to them along with their preferred payment method, they are more likely to use their preferred payment method only. Additionally, customer's inability to get credit has an impact on customer service benefit expectations for the payment methods. This can be validated through a PC value of 0.222 for SBE.

H7A: PP has a significant impact on Trust with a PC value of 0.467 which suggest that there is strong relationship between customer's availability of preferred along with other payment modes and customer's trust on the payment mode.

H7B: PP has a significant impact on PE as can be validated through a value of 0.288 for PC. This suggest that payment preference of a customer significantly affects the convenience and offer perception for the purchase.

H7C: Payment preference of the customer has a significant impact on perceived ease of use for the digital payment-based E-commerce purchases as confirmed through a PC value of 0.463

H7D: Payment method preference for customers has strong significant impact on customer perception of societal norms as confirmed through a PC value of 0.555. This signifies that customer's payment preference affects the customer's belief about other's usage of the payment method.

H7E: Payment Preference has a significant impact on Facilitating conditions as confirmed through a PC value of 0.39. This indicates that customer's payment method preference has a strong impact of

how customer perceive their knowledge & associated fraud & risk mitigation tools of the payment method when making an E-commerce transaction.

H7F: PP has a significant impact on HM as validated through a PC value of 0.531. This signifies that customer usage and benefits through his payment method preference has a strong impact on the customer fun quotient of doing an E-commerce purchase using digital payment method.

H7G: PP doesn't have any impact on number of BNPL purchases through online medium as can be seen through a low PC score of 0.009 and p value of 0.930.

H7H: While payment preference has a mildly significant impact on COD based purchases with a PC score of 0.112, the statistical significance is not validated. Also, the Q2 score is pretty low and doesn't support or reject the finding currently.

H7I: An interesting insight which was perceived here is that customer tend to have lower propensity for frequent purchases through CC if there are many payment options available. This is validated through a mildly negative PC score of -0.186.

H7J/H7K/H7L: PP doesn't have a significant impact on Debit Card / Internet Banking, Digital Wallet, and UPI based purchases as the scores are pretty low.

Table 33: Inner Model Path Coefficient IV

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Pricing -> Freq_BNPL	-0.063	-0.056	0.093	0.682	0.495

Pricing -> Freq_CC	-0.018	-0.017	0.072	0.251	0.802
Pricing -> Freq_COD	-0.032	-0.034	0.1	0.322	0.747
Pricing -> Freq_DCIB	-0.015	-0.002	0.103	0.143	0.886
Pricing -> Freq_DW	-0.087	-0.071	0.109	0.802	0.423
Pricing -> Freq_UPI	0.041	0.03	0.098	0.42	0.675
Pricing -> Payment Preference	0.135	0.143	0.125	1.075	0.282
Pricing -> SBE	0.207	0.188	0.076	2.717	0.007

H8A: Pricing has a significant impact on Payment preference of the customer which is confirmed through a PC score of 0.135. This indicates that discounts, reward, and lower fees and charges of the payment method leads to increased willingness of customer to shift to the payment method for the E-commerce purchases. Despite a slightly higher p value, this hypothesis is corroborated through a strong correlation between the construct as well as other descriptive analysis.

H8B: Pricing has a significant impact on the Service benefit expectation of the customer as validated through a PC score of 0.207. This signifies that customer's intention to make E-commerce transactions through digital method is positively affected by the pricing indicators of discount, rewards, and fees.

H8C/H8D/H8E/H8F/H8G/H8H: Pricing doesn't have a significant impact on frequency of purchases through any of the payment mode directly as indicated by low path coefficient scores. This negates our hypothesis for these cases.

Table 34: Inner Model Path Coefficient V

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
EFC-1 -> Freq_BNPL	-0.225	-0.233	0.073	3.095	0.002
EFC-1 -> Freq_CC	-0.014	-0.02	0.08	0.17	0.865
EFC-1 -> Freq_COD	0.041	0.045	0.103	0.397	0.691
EFC-1 -> Freq_DCIB	0.012	0.025	0.109	0.112	0.911
EFC-1 -> Freq_DW	-0.12	-0.133	0.086	1.394	0.163
EFC-1 -> Freq_UPI	-0.003	0.002	0.109	0.031	0.975
EFC-1 -> Payment Preference	0.082	0.101	0.098	0.84	0.401
EFC-1 -> SBE	-0.088	-0.077	0.072	1.235	0.217
EFC-2 -> Freq_BNPL	-0.142	-0.139	0.075	1.9	0.057
EFC-2 -> Freq_CC	0.05	0.046	0.073	0.681	0.496
EFC-2 -> Freq_COD	0.087	0.084	0.094	0.925	0.355
EFC-2 -> Freq_DCIB	-0.019	-0.028	0.092	0.209	0.834
EFC-2 -> Freq_DW	-0.043	-0.038	0.084	0.508	0.611
EFC-2 -> Freq_UPI	-0.012	-0.01	0.109	0.11	0.913
EFC-2 -> Payment Preference	0.273	0.255	0.098	2.793	0.005
EFC-2 -> SBE	-0.036	-0.044	0.062	0.579	0.562

H9A: EFC-1 has a mild impact on Payment preference of the customer as indicated by the bias corrected path coefficient value of 0.101. This suggest that customers take the advertisements, reviews, WOM, and other interpersonal communications positively when selecting their preferred payment method for the E-commerce transactions.

H9B: Interestingly, while customers are positively affected by external and interpersonal communications which choosing payment method, it doesn't affect their service benefit expectations for doing an e-commerce transaction using digital payment method.

H9C: EFC-1, especially interpersonal communications like WOM, reviews, and ratings have a strong negative impact on customer's propensity to do more BNPL purchases. This is indicated through a value of -0.225 for PC value.

H9D/H9E/H9F/H9G: EFC-1 doesn't have any impact on CC, COD, DCIB & UPI as indicated by their low PC scores. Interestingly, PC scores for UPI, CC, and COD were very close to zero, indicating agnostic nature for change in standard deviation of external communication.

H9H: Similar to BNPL, EFC-1 has a significant negative impact on Digital wallet-based purchases as indicated by a PC value of -0.120.

H10A: External factors & communications for environmental, geopolitical factors, and government policies has a significant impact on Payment method preference of the customer as vindicated through a strong 0.273 PC score at a p value of 0.005.

H10B: Interestingly, against for EFC-2 as well, it doesn't have a significant impact on the Service benefit expectation for E-commerce purchase through digital payment method as indicated by a small negative score of -0.036.

H10C: Environment factors, government policies, and other geopolitical factors has a significant negative impact on frequency of BNPL purchases as confirmed by a PC score of -0.142.

H10D/H10E/H10F/H10G/H10H: EFC-2 doesn't have a significant impact on frequency of COD, CC, DCIB, DW, and UPI purchases as can be seen through low PC scores which are not significant.

Table 35: Inner Model Path Coefficient VI

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AOT -> Freq_BNPL	0.274	0.28	0.098	2.78	0.005
AOT -> Freq_CC	0.065	0.07	0.082	0.79	0.429
AOT -> Freq_COD	0.017	0.015	0.117	0.142	0.887
AOT -> Freq_DCIB	-0.013	-0.027	0.118	0.109	0.913
AOT -> Freq_DW	0.161	0.158	0.106	1.527	0.127
AOT -> Freq_UPI	0.019	0.022	0.106	0.183	0.855
AOT -> Payment Preference	0.187	0.189	0.109	1.717	0.086
AOT -> SBE	-0.084	-0.068	0.079	1.06	0.289

H11A: Attributes of Tech has a significant impact on Payment method preference of the customers which is verified through a path coefficient score of 0.187. This signifies that tech factors like availability, accessibility, adaptability, merchant acceptability has a significant impact on the choice of payment method by the customer.

H11B: Again surprisingly, AOT doesn't have any significant impact on the Service benefit expectation for E-commerce purchases through digital payments of the customer.

H11C: In contrast to external factors and communications, AOT has a direct positive significant impact on frequency of BNPL purchases by a customer as can be seen through a PC score of 0.274.

H11D/ H11E/ H11F/ H11G: AOT doesn't have any significant impact on frequency of COD, CC, DCIB, and UPI based purchases as can be seen from low PC scores.

H11H: AOT has a significant impact on frequency of Digital wallet-based purchases with a PC score of 0.161

Table 36: Inner Model Path Coefficient VII

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
MOD_BNPL_ -> Freq_BNPL	0.446	0.481	0.239	1.864	0.062
MOD_CC -> Freq_CC	0.789	0.801	0.129	6.132	0
MOD_DW_ -> Freq_DW	0.18	0.176	0.16	1.125	0.261
MOD_UPI -> Freq_UPI	0.399	0.422	0.152	2.635	0.008
VALUE_GT20 -> Freq_DCIB	1.049	1.062	0.221	4.74	0
VALUE_GT20 -> Freq_DW	0.823	0.828	0.258	3.19	0.001
VALUE_GT20 -> Freq_UPI	0.368	0.366	0.268	1.374	0.169

H12: The hypothesis that Mode of Payment as BNPL for various type of purchase has a strong impact on frequency of BNPL payment method is validated with PC score of 0.446. This suggest that if any customer uses BNPL as mode of purchase for Grocery, Food delivery, and Travel then the frequency to use BNPL increases significantly.

H13: This indicator is redacted for model discriminant validity and hence won't be tested.

H14: Value of purchase more than 20K has a strong impact on frequency of CC as payment method with a indicator weight of 0.419 and path coefficient score for the construct as a strong 0.789

H15: Mode of Payment as CC for Grocery (IW: 0.346), Fashion (IW: 0.342), and Travel (0.118) has a strong impact on frequency of CC as payment method with a path coefficient score of 0.789

H16: Value of purchase greater than 20K through DCIB has PC value of more than one and hence not validated

H17: Mode of Payment for purchases of Food Delivery (IW: 0.383), Grocery (IW: 0.562), and Fashion (IW: 0.352) along with Value of Purchase more than 20K for all type of purchases (IW: 0.434) for UPI has a strong impact on frequency of UPI payment method as validated through a PC score of 0.368 for the construct Value_GT20K and 0.399 for construct MOD_UPI

H18: Mode of Payment as DW for Food delivery has a mild impact on frequency of DW as payment method with value of 0.180 for PC with slightly higher p value. On the other hand, Value of Purchase more than 20K for various type of purchase has strong impact on frequency of DW payment method as indicated through a PC value of 0.823.

H18A: This relationship is not tested in the model as the MOD_COD was redacted to validate the model.

Table 37: Inner Model Path Coefficient VIII

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Income -> Freq_BNPL	-0.066	-0.063	0.076	0.872	0.383

Income -> Freq_CC	0.211	0.205	0.105	2.004	0.045
Income -> Freq_DCIB	0.067	0.063	0.082	0.818	0.413
Income -> Freq_DW	0.125	0.13	0.085	1.469	0.142
Income -> Freq_UPI	0.093	0.087	0.133	0.704	0.482
Income -> SBE	0.001	-0.008	0.064	0.02	0.984
Income x SI -> SBE	-0.025	-0.028	0.078	0.323	0.747
Income x VALUE_GT20 -> Freq_DCIB	0.02	-0.01	0.24	0.081	0.935
Income x VALUE_GT20 -> Freq_DW	-0.05	-0.07	0.28	0.18	0.857
Income x VALUE_GT20 -> Freq_UPI	-0.098	-0.115	0.283	0.347	0.729
Income x HM -> SBE	0.067	0.06	0.095	0.711	0.477
Income x MOD_BNPL_ -> Freq_BNPL	0.236	0.209	0.251	0.937	0.349
Income x PE -> SBE	0.161	0.117	0.107	1.505	0.132
Income x FC -> SBE	0.089	0.076	0.073	1.22	0.223
Income x EE -> SBE	-0.266	-0.238	0.123	2.162	0.031
Income x MOD_UPI -> Freq_UPI	0.075	0.075	0.205	0.366	0.714
Income x MOD_CC -> Freq_CC	-0.029	-0.024	0.135	0.215	0.83
Income x MOD_DW_ -> Freq_DW	0.304	0.311	0.182	1.669	0.095

H19A: As indicated through a near neutral path coefficient, Income doesn't have any effect on service benefit expectation for E-commerce purchases by digital payment mode.

H19B: Income has a significant path coefficient value of 0.161 as moderator to the effect of Performance expectancy on SBE with close to 87% confidence interval. This indicates that with increase in income, the performance expectancy expected impact on customer's E-commerce purchase increases significantly.

H19C: With a path coefficient of -0.266, Income act as significant moderator to the effect of Effort Expectancy on SBE and with increase in income, the effort expected to ensure E-commerce purchase intention decreases significantly.

H19D / H19E / H19F / H19G: Income doesn't act as significant moderator to the effect of SI / FC / HM on SBE as validated through low path coefficient score. Income as moderator for effect of payment preference on SBE has been redacted due to model validity.

H19H: Income has a significant impact on frequency of CC Purchase as indicated through the path coefficient value of 0.211 and with increase in income, customer frequency of cc purchases is expected to increase.

H19I: Income doesn't act as a significant moderator to the effect for various type of credit card purchases on frequency of CC Purchase as negated by a low path coefficient score.

H19J: Income is validated to have significant impact on the frequency of DW Purchases as seen by a PC score of 0.125 at 84% confidence based on t-value. This suggest that with increased income, customers are more likely to increase their frequency of digital wallet purchases. Additionally,

Income also positively moderates the effect of specific type of Digital wallet purchases (Food delivery) on frequency of digital wallet purchases as confirmed by a PC score of 0.304.

H19K / H19L: As confirmed through the analysis, Income doesn't have significant impact (directly or through moderation) on the frequency of purchases for UPI & DCIB transactions which rejects our original hypothesis.

H19M: While Income do have significant path coefficient score as a moderator to the effect of type of purchase through BNPL on frequency of BNPL purchase but the corresponding t-value is extremely low and based on this we shall be rejecting our hypothesis.

Table 38: Inner Model Path Coefficient IX

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Gender -> Freq_BNPL	-0.11	-0.103	0.077	1.437	0.151
Gender -> Freq_CC	0.046	0.041	0.089	0.521	0.602
Gender -> Freq_DCIB	0.137	0.134	0.074	1.857	0.063
Gender -> Freq_DW	-0.043	-0.046	0.08	0.537	0.592
Gender -> Freq_UPI	0.062	0.068	0.107	0.576	0.564
Gender -> SBE	0	0.002	0.05	0.001	1
Gender x HM -> SBE	0.031	0.018	0.082	0.385	0.7
Gender x PE -> SBE	0.102	0.099	0.104	0.98	0.327
Gender x MOD_CC -> Freq_CC	-0.107	-0.099	0.145	0.738	0.46
Gender x EE -> SBE	-0.03	-0.012	0.091	0.334	0.738

Gender x SI -> SBE	-0.056	-0.051	0.066	0.849	0.396
Gender x MOD_DW_ -> Freq_DW	0.424	0.432	0.185	2.299	0.022
Gender x VALUE_GT20 -> Freq_DCIB	0.128	0.117	0.301	0.426	0.67
Gender x VALUE_GT20 -> Freq_DW	0.102	0.107	0.345	0.297	0.766
Gender x VALUE_GT20 -> Freq_UPI	-0.256	-0.276	0.365	0.703	0.482
Gender x MOD_UPI -> Freq_UPI	0.051	0.046	0.163	0.316	0.752
Gender x MOD_BNPL_ -> Freq_BNPL	0.35	0.319	0.225	1.556	0.12
Gender x FC -> SBE	-0.05	-0.062	0.075	0.661	0.508

H20A: This has been removed from the final model for the model validation and hence is not validated.

H20B: While path coefficient for Gender as moderator to the effect of PE on SBE is significant, the bootstrapped t-value is extremely low and hence the significance validity is negated.

H20C/ H20D /H20E / H20F: Gender doesn't act as significant moderator to the effect of EE, SI, FC, and HM on SBE as validated through low PC score.

H20G: This has been redacted from the final model to ensure model discriminant validity.

H20I: While path coefficient for Gender as a moderator to the effect for various type of credit card purchases on frequency of CC Purchase is significant at -0.107, the corresponding t-value is extremely low and thus the result is not significant.

H20J: Gender act as a significant moderator to the effect for the Food delivery through DW purchases on frequency of DW Purchase with a value of 0.424. While for Digital Wallet transactions more than 20K, the path coefficient for gender as a moderator is significant but corresponding t-values are low and this significance for the relationship is not validated.

H20K: A significantly negative path coefficient for Gender act as a moderator to the effect for transaction size of 20K+ for UPI purchases on frequency of UPI Purchase indicate a decrease in UPI purchases with change in gender. The relationship is negated due to low t-score.

H20L: Gender has a significant impact on the frequency of Debit Card / Internet banking purchases with path coefficient of 0.137. It also acts as moderator to the effect for the high value transactions of more than 20K through DCIB on frequency of DCIB Purchase.

H20M: Gender has a direct as well as moderating effect on frequency of BNPL purchases at 85% confidence level.

Table 39: Inner Model Path Coefficient X

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Age -> Freq_BNPL	-0.067	-0.058	0.096	0.692	0.489

Age -> Freq_CC	0.043	0.045	0.102	0.423	0.672
Age -> Freq_DCIB	0.07	0.065	0.078	0.899	0.368
Age -> Freq_DW	-0.006	-0.01	0.084	0.067	0.946
Age -> Freq_UPI	-0.064	-0.054	0.161	0.397	0.692
Age -> SBE	-0.044	-0.054	0.063	0.689	0.491
Age x VALUE_GT20 -> Freq_DCIB	-0.214	-0.197	0.264	0.809	0.418
Age x VALUE_GT20 -> Freq_DW	0.492	0.45	0.296	1.662	0.097
Age x VALUE_GT20 -> Freq_UPI	0.259	0.257	0.253	1.022	0.307
Age x MOD_CC -> Freq_CC	0.126	0.128	0.151	0.833	0.405
Age x SI -> SBE	-0.027	-0.03	0.089	0.302	0.763
Age x Trust -> SBE	0.021	0.033	0.079	0.27	0.787
Age x PE -> SBE	0.091	0.118	0.109	0.832	0.406
Age x MOD_DW_ -> Freq_DW	-0.169	-0.143	0.223	0.754	0.451
Age x FC -> SBE	0.075	0.075	0.072	1.037	0.3
Age x MOD_BNPL_ -> Freq_BNPL	0.132	0.131	0.226	0.585	0.559
Age x EE -> SBE	0.158	0.118	0.108	1.461	0.144
Age x MOD_UPI -> Freq_UPI	-0.093	-0.1	0.185	0.502	0.616
Age x HM -> SBE	-0.246	-0.249	0.106	2.329	0.02

H21A: Age doesn't act as significant moderator to the effect of Trust on SBE as validated through a low path coefficient score.

H21B: Age doesn't act as significant moderator to the effect of PE on SBE as validated through a low path coefficient score.

H21C: Age act as significant moderator to the effect of EE on SBE as confirmed from a positive PC value of 0.158 with a confidence of 85%

H21D: Age doesn't act as significant moderator to the effect of SI on SBE as validated through a low path coefficient score.

H21E: Age doesn't act as significant moderator to the effect of FC on SBE as validated through a low path coefficient score.

H21F: Age act as significant moderator to the effect of HM on SBE with an increase in age decreases the impact of hedonic motivation on customer purchase intention. This is validated with a negative path coefficient score of -0.246 at 95% confidence.

H21G: Relationship of Age as a moderator to PP on SBE has been redacted for model validation.

H21H: Age doesn't have significant impact on Frequency of purchases with CC as payment mode as seen from low PC score.

H21I: Age act as a significant moderator to the effect of Grocery, Fashion, and travel related transactions by credit card on frequency of CC Purchase with a PC score of 0.126.

H21J: Age does have a significant impact on frequency of digital wallet purchases but do act as a significant moderator to the effect of high value transaction of more than 20K through Digital wallet on frequency of DW Purchase with a path coefficient score of 0.492 at 95% confidence.

H21K: Age doesn't act as a significant moderator to the effect for the various type and value of UPI purchases on frequency of UPI Purchase as can be seen through low PC scores except for moderating the significance of high value transactions through UPI on customer purchase intentions with a PC score of 0.256.

H21L: Age negatively moderates the effect of high value transactions of more than 20K through Debit card / Internet banking on frequency of DCIB Purchase with a PC score of -0.214.

H21M: Age mildly moderates the effect of type of purchase through BNPL on frequency of BNPL purchase as validated through a PC score of 0.132.

H22: Choice of payment do have a moderating impact on both Online purchase intention and online purchase behaviour as can be validated through the significant impact of payment preference on SBE as well as on the frequency of purchases for various type of payments.

Table 40: Hypothesis Summary

Hypothesis	Validation	Relationship
H1: PE has a significant impact on SBE for choice of payment method in E-commerce	Accepted	Positive
H2: Effort Expectancy has a significant impact on E-commerce Service benefit expectation	Accepted	Positive

H2A: Effort Expectancy has a significant impact on the Performance expectancy for the choice of payment method in an E-commerce purchase	Accepted	Positive
H3: Social Influence has a significant impact on E-commerce service benefit expectation	Accepted	Negative
H3A: Social Influence has a significant impact on Effort expectancy	Accepted	Positive
H3B: Social Influence has a significant impact on Facilitating condition	Accepted	Positive
H4: Facilitating Condition has a significant impact on E-commerce purchase intention	Accepted	Positive
H4A: Facilitating Condition has a significant impact on Hedonic motivation	Accepted	Positive
H5: HM has a significant impact on customer's digital payment behaviour intentions for E-commerce purchases.	Rejected	
H6: Trust has a significant impact on E-commerce SBE.	Accepted	Positive
H6A: Trust has a significant impact on Performance Expectancy.	Accepted	Positive
H7: Payment preference has a significant impact on the Service benefit expectation	Accepted	Positive
H7A: PP has a significant impact on Trust	Accepted	Positive
H7B: PP has a significant impact on PE	Accepted	Positive
H7C: PP has a significant impact on EE	Accepted	Positive
H7D: PP has a significant impact on SI	Accepted	Positive
H7E: PP has a significant impact on FC	Accepted	Positive
H7F: PP has a significant impact on HM	Accepted	Positive
H7G: PP has a significant impact on BNPL purchases	Rejected	

H7H: PP has a significant impact on COD based purchases	Borderline	
H7I: PP has a significant impact on CC based purchases	Accepted	Negative
H7J: PP has a significant impact on Debit Card / Internet Banking based purchases	Rejected	
H7K: PP has a significant impact on UPI based purchases	Rejected	
H7L: PP has a significant impact on Digital wallet based purchases	Rejected	
H8A: Pricing has a significant impact on Payment preference of the customer	Accepted	Positive
H8B: Pricing has a significant impact on the Service benefit expectation of the customer	Accepted	Positive
H8C: Pricing has a significant impact on BNPL purchases	Rejected	
H8D: Pricing has a significant impact on COD based purchases	Rejected	
H8E: Pricing has a significant impact on CC based purchases	Rejected	
H8F: Pricing has a significant impact on Debit Card / Internet Banking based purchases	Rejected	
H8G: Pricing has a significant impact on UPI based purchases	Rejected	
H8H: Pricing has a significant impact on Digital wallet-based purchases	Rejected	
H9A: EFC-1 has a significant impact on Payment preference of the customer	Accepted	Positive
H9B: EFC-1 has a significant impact on the Service benefit expectation of the customer	Rejected	
H9C: EFC-1 has a significant impact on BNPL purchases	Accepted	Negative
H9D: EFC-1 has a significant impact on COD based purchases	Rejected	
H9E: EFC-1 has a significant impact on CC based purchases	Rejected	

H9F: EFC-1 has a significant impact on Debit Card / Internet Banking based purchases	Rejected	
H9G: EFC-1 has a significant impact on UPI based purchases	Rejected	
H9H: EFC-1 has a significant impact on Digital wallet-based purchases	Accepted	Negative
H10A: EFC-2 has a significant impact on Payment preference of the customer	Accepted	Positive
H10B: EFC-2 has a significant impact on the Service benefit expectation of the customer	Rejected	
H10C: EFC-2 has a significant impact on BNPL purchases	Accepted	Negative
H10D: EFC-2 has a significant impact on COD based purchases	Rejected	
H10E: EFC-2 has a significant impact on CC based purchases	Rejected	
H10F: EFC-2 has a significant impact on Debit Card / Internet Banking based purchases	Rejected	
H10G: EFC-2 has a significant impact on UPI based purchases	Rejected	
H10H: EFC-2 has a significant impact on Digital wallet-based purchases	Rejected	
H11A: AOT has a significant impact on Payment preference of the customer	Accepted	Positive
H11B: AOT has a significant impact on the Service benefit expectation of the customer	Rejected	
H11C: AOT has a significant impact on BNPL purchases	Accepted	Positive
H11D: AOT has a significant impact on COD based purchases	Rejected	
H11E: AOT has a significant impact on CC based purchases	Rejected	

H11F: AOT has a significant impact on Debit Card / Internet Banking based purchases	Rejected	
H11G: AOT has a significant impact on UPI based purchases	Rejected	
H11H: AOT has a significant impact on Digital wallet-based purchases	Accepted	Positive
H12: Mode of Payment for various type of purchase has a strong impact on frequency of BNPL payment method	Accepted	Positive
H13: Value of Purchase for various type of purchase has a strong impact on frequency of BNPL payment method	Redacted	
H14: Value of purchase for various purchase type has a strong impact on frequency of CC as payment method	Accepted	Positive
H15: Mode of Payment for various purchase type has a strong impact on frequency of CC as payment method	Accepted	Positive
H16: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of DCIB payment method	Rejected	
H17: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of UPI payment method.	Accepted	Positive
H18: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of DW payment method.	Accepted	Positive
H18A: Mode of Payment & Value of Purchase for various type of purchase has a strong impact on frequency of COD payment method.	Redacted	
H19A: Income has a significant impact on SBE	Rejected	
H19B: Income act as significant moderator to the effect of Performance expectancy on SBE	Accepted	Positive

H19C: Income act as significant moderator to the effect of Effort Expectancy on SBE	Accepted	Negative
H19D: Income act as significant moderator to the effect of SI on SBE	Rejected	
H19E: Income act as significant moderator to the effect of FC on SBE	Rejected	
H19F: Income act as significant moderator to the effect of HM on SBE	Rejected	
H19G: Income act as significant moderator to the effect of Payment Preference on SBE	Rejected	
H19H: Income act as a significant moderator to the effect of value of purchase on frequency of CC Purchase	Accepted	Positive
H19I: Income act as a significant moderator to the effect for various type of credit card purchases on frequency of CC Purchase	Rejected	
H19J: Income act as a significant moderator to the effect for the various type and value of DW purchases on frequency of DW Purchase	Borderline	
H19K: Income act as a significant moderator to the effect for the various type and value of UPI purchases on frequency of UPI Purchase	Rejected	
H19L: Income act as a significant moderator to the effect for the various type and value of DCIB purchases on frequency of DCIB Purchase	Rejected	
H19M: Income act as a significant moderator to the effect of type of purchase through BNPL on frequency of BNPL purchase	Rejected	

H20A: Gender act as significant moderator to the effect of Trust on SBE	Redacted	
H20B: Gender act as significant moderator to the effect of PE on SBE	Rejected	
H20C: Gender act as significant moderator to the effect of EE on SBE	Rejected	
H20D: Gender act as significant moderator to the effect of SI on SBE	Rejected	
H20E: Gender act as significant moderator to the effect of FC on SBE	Rejected	
H20F: Gender act as significant moderator to the effect of HM on SBE	Rejected	
H20G: Gender act as significant moderator to the effect of Payment Preference on SBE	Redacted	
H20I: Gender act as a significant moderator to the effect for various type of credit card purchases on frequency of CC Purchase	Rejected	
H20J: Gender act as a significant moderator to the effect for the various type and value of DW purchases on frequency of DW Purchase	Accepted	Positive
H20K: Gender act as a significant moderator to the effect for the various type and value of UPI purchases on frequency of UPI Purchase	Rejected	
H20L: Gender act as a significant moderator to the effect for the various type and value of DCIB purchases on frequency of DCIB Purchase	Accepted	Positive

H20M: Gender act as a significant moderator to the effect of type of purchase through BNPL on frequency of BNPL purchase	Accepted	Positive
H21A: Age act as significant moderator to the effect of Trust on SBE	Rejected	
H21B: Age act as significant moderator to the effect of PE on SBE	Rejected	
H21C: Age act as significant moderator to the effect of EE on SBE	Accepted	Positive
H21D: Age act as significant moderator to the effect of SI on SBE	Rejected	
H21E: Age act as significant moderator to the effect of FC on SBE	Rejected	
H21F: Age act as significant moderator to the effect of HM on SBE	Accepted	Negative
H21G: Age act as significant moderator to the effect of PP on SBE	Redacted	
H21H: Age act as a significant moderator to the effect of value of purchase on frequency of CC Purchase	Rejected	
H21I: Age act as a significant moderator to the effect for various type of credit card purchases on frequency of CC Purchase	Accepted	Positive
H21J: Age act as a significant moderator to the effect for the various type and value of DW purchases on frequency of DW Purchase	Accepted	Positive
H21K: Age act as a significant moderator to the effect for the various type and value of UPI purchases on frequency of UPI Purchase	Accepted	Positive
H21L: Age act as a significant moderator to the effect for the various type and value of DCIB purchases on frequency of DCIB Purchase	Accepted	Negative
H21M: Age act as a significant moderator to the effect of type of purchase through BNPL on frequency of BNPL purchase	Accepted	Positive
H22: Choice of payment has a moderating impact on both Online purchase intention and online purchase behaviour.	Accepted	Positive

4.6. Results:

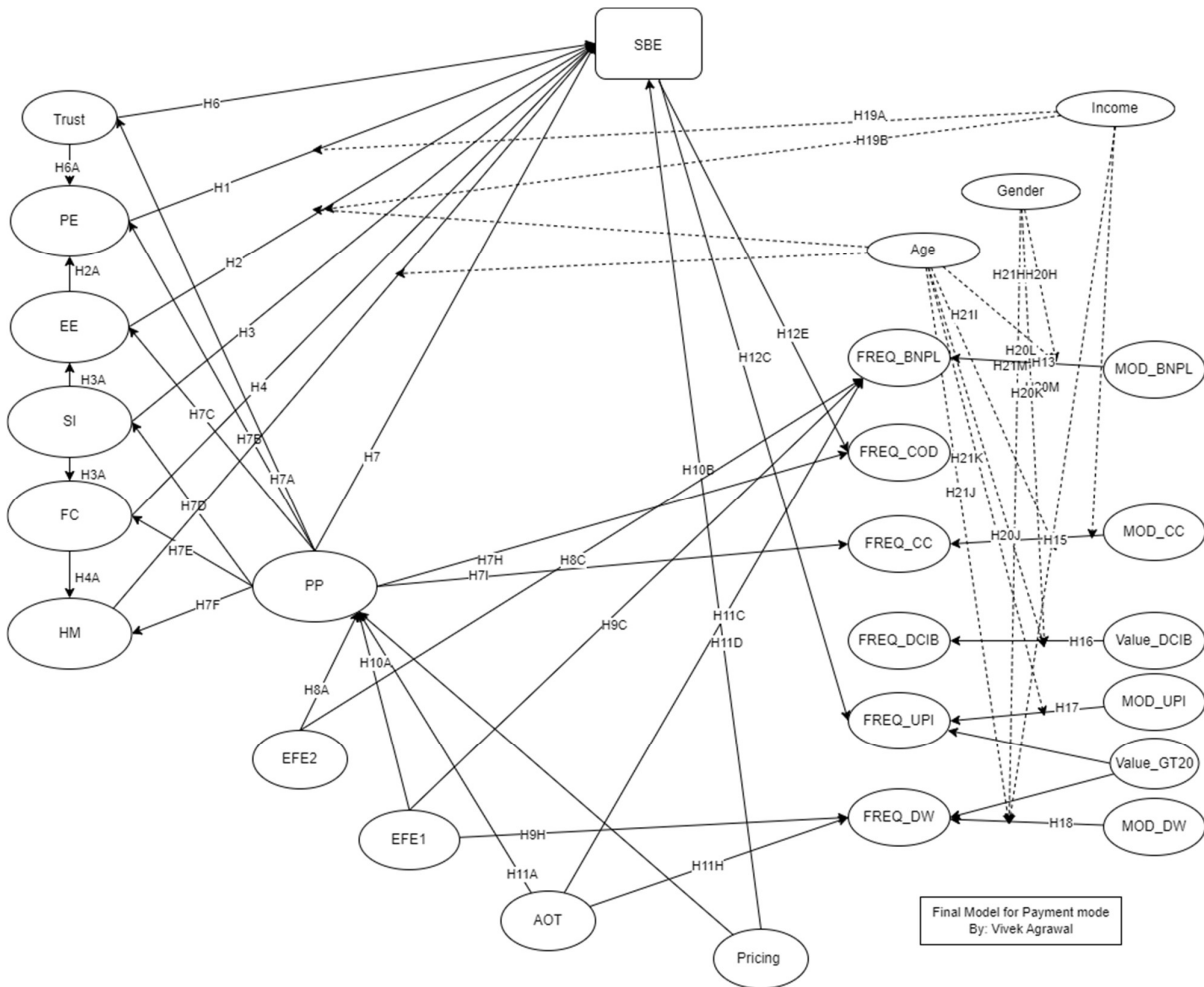


Figure 21: Final Revised Model

Based on final analysis, a final model has been prepared considering all the significant factors. Payment Preference is significantly affected by External communication, environmental factors, Attributes of Tech, and Pricing. Trust, PE, EE, FC, PP, and Pricing have a strong positive affect on SBE, while SI exerts a negative impact. On the other hand, HM doesn't directly affect SBE significantly but when moderated by Age has a strong effect on customer's service benefit expectations. Payment Preference has strong impact on Trust, PE, EE, SI, FC, HM, and SBE. Additionally, PP also impacts frequency of purchases using CC and COD, while it doesn't impact BNPL, Debit Card / Internet Banking, UPI, and Digital Wallet purchases. Service Benefit

Expectation of a customer impacts the frequency of purchases through COD and UPI, but doesn't affect frequency of purchases through other mode of purchases. Interestingly, EFC2, EFC1, and AOT affects frequency of purchases through BNPL, while EFC1 and AOT also impacts frequency of purchases through Digital Wallets. Age has a significant moderating impact on the way mode of purchase affect frequency of purchases for BNPL, CC, DC/IB, UPI, and Wallets. Additionally, Age also moderates EE and HM. Gender doesn't have impact on any of the STATE variables directly, while it has a moderating effect on frequency of purchases through mode of purchases as BNPL, DCIB, and Digital Wallet. Income has a moderating effect on PE and EE. Additionally, it also moderates the frequency of purchases through CC and Digital wallet as mode of purchase.

4.6.1. Research Question 1:

The RQ1 is answered and validated through the introduction and significance of the Payment Preference construct for all model constructs of E-commerce. PP1 is positively correlated to BI2 (PP1xBI2:0.188) suggesting that customer payment choice positively affects discounts / offers by the E-commerce website. The study also confirms that having multiple payment options with good limit and facilities promotes (PP3xBI2:0.490) customer to switch if competition is offering better discounts. Additionally, the study also corroborates that the customer perception to having and using a credit card positively affects (PP2xBI3:0.322) customer probability to switch in case of restriction on choice of payment method. This customer behaviour is further corroborated through This is also positively associated (PP2xBI6:0.386) with the intention to stop using credit card over the E-commerce website security concerns. On the other hand, having multiple payment options negatively affects the risk appetite of customers (PP3xBI6:0.306). Customer expectation about merchants having the customer's preferred payment method strongly affects customer behaviour intention to switch from the merchant in case the preferred payment method cease to be offered by the E-commerce

website. The stronger correlation suggest that customer have a higher tendency to switch in case of absence of payment method than through offer / discount.

Table 41: PPxSBE

PP	Question	SBE	Questions	Correlation
PP1	I mostly use one specific Digital payment method for my online purchase	BI2	I will switch to a rival E-comm site /app if it offers me good discounts on Digital payment methods	0.188
PP1	I mostly use one specific Digital payment method for my online purchase	BI3	I will switch purchases from my regular website if it stops offering my preferred payment method	0.299
PP1	I mostly use one specific Digital payment method for my online purchase	BI5	I am likely to cancel the purchase at checkout if the payment method looks suspicious	0.224
PP1	I mostly use one specific Digital payment method for my online purchase	BI6	I will not buy from secured E-comm websites if it stops providing secure payment methods.	0.206
PP2	I believe that not having a credit card limits online purchases capacity	BI2	I will switch to a rival E-comm site /app if it offers me good discounts on Digital payment methods	0.397
PP2	I believe that not having a credit card limits online purchases capacity	BI3	I will switch purchases from my regular website if it stops offering my preferred payment method	0.322
PP2	I believe that not having a credit	BI5	I am likely to cancel the purchase	0.309

	card limits online purchases capacity		at checkout if the payment method looks suspicious	
PP2	I believe that not having a credit card limits online purchases capacity	BI6	I will not buy from secured E-comm websites if it stops providing secure payment methods.	0.3860
PP3	Having multiple payment options with good credit limit & EMI gives me confidence to purchase online	BI2	I will switch to a rival E-comm site /app if it offers me good discounts on Digital payment methods	0.4900
PP3	Having multiple payment options with good credit limit & EMI gives me confidence to purchase online	BI3	I will switch purchases from my regular website if it stops offering my preferred payment method	0.466
PP3	Having multiple payment options with good credit limit & EMI gives me confidence to purchase online	BI5	I am likely to cancel the purchase at checkout if the payment method looks suspicious	0.253
PP3	Having multiple payment options with good credit limit & EMI gives me confidence to purchase online	BI6	I will not buy from secured E-comm websites if it stops providing secure payment methods.	0.306
PP4	I expect E-commerce site / App to have my preferred payment method	BI2	I will switch to a rival E-comm site /app if it offers me good discounts on Digital payment	0.377

			methods	
PP4	I expect E-commerce site / App to have my preferred payment method	BI3	I will switch purchases from my regular website if it stops offering my preferred payment method	0.439
PP4	I expect E-commerce site / App to have my preferred payment method	BI5	I am likely to cancel the purchase at checkout if the payment method looks suspicious	0.357
PP4	I expect E-commerce site / App to have my preferred payment method	BI6	I will not buy from secured E-comm websites if it stops providing secure payment methods.	0.303

In addition to above, the Payment Preference also have significant positive impact on Trust, PE, EE, SI, FC, HM as has been validated through Hypothesis H7, and H7A to H7F, earlier in the research. This along with a positive impact of pricing on customer purchase intention validates the RQ1.

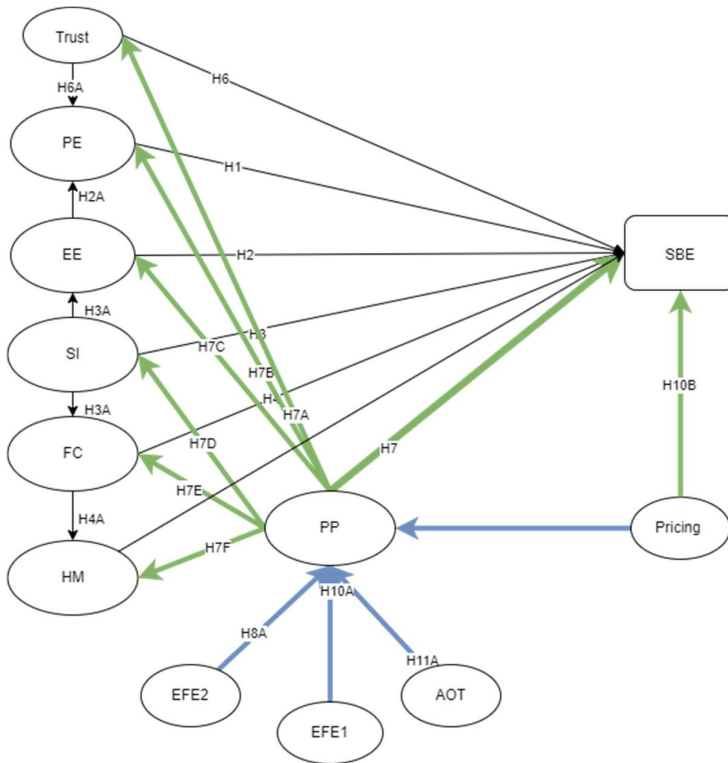


Figure 22: Payment Preference impact on E-commerce

4.6.2. Research Question 2:

RQ2 is promulgated through the extensive literature review wherein the author has presented impact of various payment methods on the E-commerce purchases. This is further validated through the Hierarchical clustering wherein the final clusters have been identified through dendrogram study and it has been deduced that customer E-commerce purchase varies with mode of purchase which is further moderated by type of purchase and value of purchase. This has been verified through the model via hypothesis H12 to H18 which suggest that different mode of payment affect the customer purchase frequency differently.

For RQ2, 2nd part, it can be seen that the significant factors attributed through different segmentations features impacts purchases through various payment mode differently. From the validated model, following insights have been extracted based of correlation values:

The correlation values suggest that frequency of purchases for different mode of purchases varies significantly with different indicators.

- There is a small correlation between older age and increase in frequency of CC purchases while this is not the case for other payment mode
- There is a strong correlation between higher income and increase in frequency of CC purchase while for COD, UPI, and DW there is weak but positive correlation. For BNPL, there exist a negative correlation indicating low-income customers tend to do more BNPL purchases. The correlation is very minimal for DC/IB.
- There exists a distinct difference in purchase pattern between CC and COD based on gender with Male customer are more likely to have more purchases using credit card while female customers prefer COD as their choice of payment mode. The correlation is extremely weak for other payment modes.
- Customers who switch due to offers / discounts are likely to do more CC Purchases. The impact of discount/ offers is extremely low on other payment modes.
- Customers believe that Government policy doesn't affect purchases through COD while they are neutral on its impact on other mode of payment.
- WOM is not considered important for COD while it is an important factor for UPI and BNPL.
- Demographic variables (Age, Gender, and Income) moderate the usage of UPI purchases when customer is having accessibility to UPI as mode of payment. An important highlight is that customer usage for CC is also affected by this moderation on UPI suggesting a use case for UPI on CC product.
- Promotion and advertisements have a mild effect on BNPL purchases.
- Reviews have a small effect on BNPL and Debit Card / Internet Banking purchases
- Rewards leads to increase in frequency of purchases for UPI and Credit Card

- Customers strongly agrees that higher Merchant Acceptability of Credit Card leads to increase in frequency of CC purchases.

Table 42: Correlation matrix for Freq of Purchase using different mode of payment

indicators	COD	CC	DC/IB	UPI	DW	BNPL
1clickPayment	-0.027	-0.015	-0.089	-0.054	-0.123	-0.043
Age	0.038	0.303	-0.004	-0.040	0.052	-0.066
BI2	-0.044	-0.238	0.042	-0.069	-0.083	0.033
BI3	-0.046	-0.166	0.019	-0.051	-0.016	-0.062
BI5	-0.058	-0.300	0.039	-0.135	-0.079	0.078
BI6	0.029	-0.170	0.020	-0.023	0.029	0.138
Discount	-0.022	-0.229	0.046	-0.040	-0.071	-0.004
EE2	0.079	-0.139	-0.043	-0.110	-0.054	0.072
EE3	0.056	-0.228	0.000	-0.066	0.019	0.135
Ease_payment	0.037	-0.116	0.059	-0.062	-0.005	0.028
FC1	-0.076	-0.194	-0.061	-0.097	0.045	0.022
FC4	-0.048	-0.172	-0.003	-0.096	0.023	0.111
Gender	0.125	-0.177	0.082	-0.006	-0.031	-0.043
Geopolitical	0.074	-0.079	-0.030	-0.055	-0.075	-0.130
Govern_Policy	0.143	-0.027	-0.070	0.002	-0.027	-0.076
HM1	0.013	-0.338	0.005	-0.111	-0.019	0.021
HM2	0.122	-0.189	-0.054	-0.009	-0.033	-0.090
High_security	-0.007	-0.112	-0.115	-0.006	-0.119	0.070
Income	0.139	0.426	0.076	0.144	0.194	-0.128

Merc_Acce	0.078	-0.240	-0.079	-0.051	-0.040	0.092
PE1	-0.004	-0.276	-0.050	-0.035	0.016	0.033
PE3	0.026	-0.225	-0.038	-0.098	-0.018	0.013
PP1	0.016	-0.070	-0.116	-0.074	-0.057	0.043
PP2	0.118	-0.259	0.090	-0.003	0.027	-0.032
PP3	0.100	-0.220	0.007	-0.023	-0.014	-0.020
PP4	-0.024	-0.261	-0.019	-0.146	-0.052	0.010
Promo_Advert	0.098	-0.079	-0.072	-0.056	-0.082	-0.154
Reviews	-0.046	-0.082	-0.112	-0.035	-0.070	-0.137
Rewards	0.026	-0.184	-0.064	0.020	-0.134	-0.022
SI1	0.040	-0.164	0.050	-0.029	0.026	-0.026
Si2	0.064	-0.100	0.000	0.009	-0.003	-0.110
T1	0.088	-0.030	0.069	0.027	0.030	0.020
T2	-0.047	-0.161	-0.024	-0.082	0.012	0.096
UI_CX	0.039	-0.222	-0.031	-0.051	-0.004	0.068
WOM	0.138	0.010	0.052	0.039	-0.092	-0.103
Widespread_availability	0.128	-0.106	-0.041	-0.040	-0.026	0.084
Income x VALUE_GT20	0.156	0.172	0.085	0.115	0.194	-0.139
Age x MOD_BNPL_	0.057	0.101	0.017	-0.054	0.038	0.008
Gender x FC	0.016	0.108	0.090	-0.002	0.169	-0.017
Income x SI	-0.088	0.005	0.052	0.050	0.039	-0.037
Gender x SI	-0.020	-0.051	0.029	-0.042	0.099	-0.019
Income x HM	0.082	-0.021	0.248	0.112	0.075	0.034
Income x MOD_UPI	0.131	0.322	0.014	0.105	0.145	-0.137
Gender x MOD_CC	0.073	-0.265	0.008	-0.032	-0.030	-0.089

Age x SI	0.109	0.113	0.039	0.070	-0.032	-0.002
Age x HM	0.128	0.143	0.238	0.081	0.102	0.048
Age x EE	0.014	0.139	0.108	0.021	0.012	-0.033
Income x FC	0.032	-0.015	0.163	0.123	-0.026	-0.066
Age x MOD_UPI	0.114	0.276	-0.014	-0.048	0.090	0.000
Gender x VALUE_GT20	-0.045	-0.169	-0.070	-0.145	-0.105	-0.096
Income x MOD_BNPL_	0.044	0.221	0.038	0.073	0.044	-0.040
Age x FC	0.126	0.124	0.169	0.058	-0.076	-0.072
Gender x Payment Preference	-0.043	-0.087	0.086	0.032	0.048	-0.022
Income x EE	-0.046	-0.031	0.050	0.046	-0.016	-0.030
Income x Payment Preference	-0.004	-0.040	0.164	0.089	0.064	-0.077
Gender x MOD_DW_	0.024	-0.197	0.006	-0.031	0.067	-0.062
Gender x PE	0.049	-0.095	0.055	0.052	0.040	-0.036
Age x Trust	0.122	0.105	0.103	0.051	0.019	0.051
Gender x MOD_BNPL_	-0.074	-0.096	-0.045	-0.092	-0.024	0.062
Gender x HM	0.063	-0.101	0.082	0.081	0.056	-0.025
Age x PE	0.136	0.160	0.190	0.120	0.082	-0.025
Income x MOD_CC	0.026	0.390	-0.035	0.085	0.101	-0.158
Age x Payment Preference	0.079	0.138	0.134	0.008	0.020	-0.020
Income x PE	0.043	0.004	0.098	0.042	0.052	0.002
Age x VALUE_GT20	0.197	0.097	-0.060	0.032	0.103	-0.039

Income x MOD_DW_	0.146	0.244	0.039	0.076	0.176	-0.135
Age x MOD_DW_	0.099	0.053	-0.073	-0.036	-0.011	-0.013
Gender x MOD_UPI	0.105	-0.136	0.101	-0.009	0.024	-0.077
Age x MOD_CC	0.011	0.318	-0.109	-0.034	-0.083	-0.088
Gender x EE	0.031	-0.052	0.042	-0.029	0.090	0.003

Similarly, as discussed earlier in the research, the type of purchase also affects the mode of payment for the customer intentions:

- Grocery, Travel and High value purchases through CC tends to increase with increase in Age while young age people tend to use UPI for Fashion purchases
- Customers are affected by discounts for CC purchases for grocery and also for values greater than 20K
- Male customers are more likely to use CC for Fashion and high value purchases.
- CC purchases for Fashion, Travel, Food Delivery, and high value purchases, in addition to UPI purchases of Food Delivery, and Grocery increases with increase in Income. BNPL purchases are slightly negatively associated with Income.
- High value and Fashion purchases using CC are believed to be impacted by merchant acceptability.
- Convenience is a factor for all Credit card purchases irrespective of type and value of purchases.
- Reward seeking customers have less tendency to use UPI for fashion purchases while no impact on Food delivery and grocery. CC Purchases of Food delivery and Fashion along with BNPL food delivery tends to be done by such customers.
- Higher income customers are more likely to use BNPL related Travel expenses for Convenience and Discounts.

Table 43: Correlation Type of Purchase

Indicators	BNPL			CC				DW			UPI			DC IB
	FD	G R	TR VL	Fas hio n	G R	TR VL	GT 20 K	FD	Fas hio n	GT 20 K	FD	G R	GT 20 K	GT 20 K
1clickPayment	- 0.0 77	- 0.1 03	- 0.1 08	0.0 18	- 0.0 60	- 0.0 46	- 0.0 54	- 0.1 27	0.0 72	- 0.1 10	- 0.0 05	- 0.0 60	- 0.0 79	0.0 34
Age	- 0.0 70	- 0.0 34	0.0 59	0.0 70	0.1 75	0.1 79	0.2 15	0.0 32	- 0.1 05	0.0 53	0.0 63	- 0.0 32	- 0.0 40	- 0.0 84
BI2	- 0.0 04	0.0 25	- 0.0 94	- 0.0 94	- 0.0 47	- 0.0 41	- 0.1 42	- 0.0 97	0.1 00	- 0.1 05	- 0.1 07	0.0 39	0.0 55	- 0.0 90
BI3	0.0 07	0.0 11	0.0 19	- 0.0 40	- 0.0 93	- 0.0 02	- 0.0 69	0.0 71	0.0 14	- 0.0 13	0.0 16	0.0 45	0.0 01	0.0 30
BI5	0.0 67	0.0 98	- 0.0 05	- 0.1 34	- 0.0 76	- 0.1 47	- 0.2 75	- 0.1 48	0.0 85	- 0.1 24	- 0.2 07	- 0.0 86	- 0.0 47	0.0 19
BI6	0.0 05	0.0 58	- 0.0 32	- 0.0 19	- 0.1 64	- 0.0 36	- 0.1 73	- 0.0 43	0.0 06	- 0.0 14	- 0.1 16	- 0.0 17	0.0 26	0.0 25
Discount	0.0	-	-	-	-	-	-	-	0.0	-	-	-	-	-

	13	0.0	0.0	0.1	0.2	0.0	0.2	0.0	88	0.1	0.0	0.0	0.0	0.0
		38	14	72	10	73	77	56		02	22	68	66	28
EE2	0.1	0.0	0.0	-	-	-	-	-	0.0	-	-	-	-	-
	04	34	90	0.0	0.0	0.0	0.1	0.0	13	0.0	0.0	0.0	0.0	0.0
				49	13	35	15	19		76	82	73	42	86
EE3	0.0	0.0	0.0	-	-	-	-	-	0.0	-	-	0.0	0.0	-
	40	68	21	0.1	0.0	0.0	0.1	0.0	10	0.0	0.1	0.0	0.0	0.0
				14	72	64	70	19		37	24	25	28	32
Ease_payment	-	-	-	-	-	-	-	-	0.0	-	-	0.0	-	-
	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.0	66	0.0	0.0	0.0	0.0	0.0
	18	56	25	19	68	63	34	34	67	84	58	81	87	06
FC1	0.1	0.0	0.0	-	-	-	-	-	-	-	-	-	-	-
	07	11	56	0.1	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0
				18	31	59	62	30	51	86	77	46	70	51
FC4	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	0.0	0.0	0.0	0.1	0.1	0.1	0.2	0.0	0.0	0.0	0.1	0.1	0.0	0.0
	23	03	56	30	58	85	04	66	04	72	93	92	32	31
Gender	0.0	0.0	0.0	-	-	-	-	-	-	-	-	-	-	-
	60	37	45	0.2	0.1	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
				21	38	92	98	21	14	34	48	07	15	08
Geopolitical	0.0	-	0.1	-	-	0.0	0.0	0.0	-	-	0.0	0.0	-	0.0
	77	0.1	02	0.0	0.1	93	41	01	0.0	0.0	33	29	0.1	0.0
		11		51	16				63	35			70	11
Govern_Policy	-	-	0.0	-	0.0	0.0	-	0.0	-	-	0.0	-	-	-
	0.0	0.0	59	0.0	05	69	0.1	02	0.0	0.0	45	0.0	0.1	0.1

	08	28		40			47		31	75		73	24	59
HM1	0.0 63	0.0 55	- 0.0 13	- 0.1 96	- 0.1 44	- 0.0 80	- 0.2 57	0.0 01	0.0 08	- 0.0 46	- 0.0 92	- 0.0 67	- 0.0 71	- 0.0 57
HM2	- 0.0 43	- 0.0 93	- 0.0 57	- 0.1 37	- 0.1 22	- 0.0 80	- 0.0 42	- 0.0 01	- 0.1 11	0.1 12	- 0.0 79	- 0.0 70	- 0.0 04	- 0.0 55
High_security	- 0.0 25	0.0 01	- 0.1 17	- 0.2 30	- 0.1 95	- 0.1 59	- 0.2 12	- 0.0 98	- 0.0 25	- 0.1 42	- 0.0 49	- 0.0 06	- 0.2 00	- 0.0 72
Income	- 0.1 02	- 0.1 53	- 0.0 03	0.2 69	0.1 19	0.3 05	0.3 94	0.1 88	0.0 32	0.0 44	0.1 84	0.1 66	0.0 03	0.1 10
Merc_Acce	0.0 38	- 0.0 48	- 0.0 33	- 0.1 89	- 0.1 57	- 0.0 57	- 0.2 37	- 0.1 15	- 0.1 25	- 0.0 87	- 0.0 66	- 0.1 27	- 0.1 32	- 0.1 30
PE1	- 0.0 47	- 0.0 71	- 0.0 69	- 0.1 91	- 0.1 85	- 0.1 79	- 0.2 07	- 0.0 74	- 0.0 45	0.0 00	- 0.0 97	- 0.0 72	0.0 10	- 0.0 90
PE3	0.0 47	0.0 43	0.0 02	- 0.1 21	- 0.0 51	- 0.0 01	- 0.1 94	0.0 39	0.0 58	- 0.0 29	0.0 00	- 0.0 32	0.0 13	- 0.0 75
PP1	0.0 03	- 0.0 68	- 0.1 28	- 0.0 15	0.0 15	- 0.0 12	- 0.0 51	- 0.0 45	- 0.0 26	- 0.1 05	- 0.1 56	- 0.0 33	- 0.1 14	- 0.1 02

	-	-	-	-	-	-	-	-	-	-	-	-	-	-
PP2	0.1	0.1	0.1	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0
	21	40	35	98	77	23	10	92	17	60	64	65	36	17
PP3	-	-	-	-	-	-	-	-	-	0.0	-	-	-	-
	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	44	0.0	0.0	0.0	0.0
	72	18	57	13	88	19	26	27	15		27	66	10	34
PP4	0.0	0.0	0.0	-	-	-	-	0.0	0.0	-	-	-	0.0	-
	84	66	47	0.0	0.0	0.0	0.1	22	22	0.0	0.1	0.0	0.0	0.0
				29	59	19	15			15	11	28	08	34
Promo_Advert	-	-	0.1	-	-	0.0	-	-	0.0	-	0.0	-	-	-
	0.0	0.1	24	0.0	0.0	32	0.0	0.0	46	0.0	29	0.0	0.1	0.0
	29	09		57	61		21	02		36		34	98	56
Reviews	-	-	-	-	-	0.0	-	0.0	0.0	-	0.0	-	-	-
	0.0	0.0	0.0	0.0	0.0	40	0.1	00	53	0.1	20	0.0	0.1	0.0
	33	26	46	28	18		09			32		52	97	97
Rewards	-	-	-	-	-	-	-	-	0.1	-	0.0	-	-	-
	0.0	0.1	0.0	0.1	0.2	0.0	0.1	0.0	48	0.1	02	0.0	0.1	0.0
	47	20	51	33	14	48	96	67		09		08	32	26
SI1	0.0	0.0	0.1	-	-	-	-	0.0	0.0	-	-	-	-	-
	81	00	62	0.1	0.1	0.0	0.1	83	17	0.0	0.0	0.1	0.0	0.0
				37	21	55	01			79	55	06	20	69
SI2	0.0	-	0.0	0.0	-	0.0	-	0.1	0.1	-	-	0.0	0.0	-
	48	0.0	49	50	0.0	94	0.0	15	02	0.0	0.0	50	46	0.0
		05			73		67			35	17			32
T1	-	-	-	0.0	-	-	-	-	0.0	-	-	-	-	-

	0.0 33	0.0 06	0.0 12	19	0.1 23	0.0 62	0.1 43	0.0 51	27	0.0 83	0.1 24	0.0 47	0.0 13	0.0 11
T2	0.0 81	0.0 65	- 0.0 03	- 0.0 63	- 0.1 04	- 0.0 62	- 0.2 18	- 0.0 67	0.0 33	- 0.0 68	- 0.1 07	- 0.1 18	- 0.0 49	- 0.0 28
UI_CX	- 0.0 13	- 0.0 69	- 0.0 10	- 0.1 16	- 0.1 48	- 0.0 96	- 0.2 32	- 0.0 01	0.0 42	- 0.1 14	- 0.0 19	- 0.1 32	- 0.0 97	- 0.0 54
WOM	- 0.0 16	- 0.0 75	- 0.0 15	0.0 44	0.0 26	- 0.0 46	- 0.0 50	- 0.0 75	0.1 15	- 0.1 44	0.0 29	0.0 36	- 0.1 10	- 0.0 17
Widespread_av ailability	0.1 20	0.0 27	0.0 83	- 0.1 28	- 0.0 90	- 0.0 06	- 0.2 01	0.0 43	- 0.0 37	- 0.1 08	0.0 57	- 0.0 58	- 0.0 70	- 0.0 83
Income x VALUE_GT20	- 0.0 16	- 0.0 99	- 0.0 22	0.0 65	- 0.0 97	0.0 98	0.2 39	0.1 59	0.0 28	0.2 11	0.1 29	0.0 81	0.1 04	0.2 49
Age x MOD_BNPL_	- 0.0 69	- 0.0 05	0.0 58	- 0.0 53	0.0 15	- 0.0 69	0.1 00	- 0.0 95	- 0.0 78	0.0 56	0.0 27	0.0 11	- 0.0 08	- 0.0 10
Gender x FC	0.1 18	0.0 82	0.0 13	0.1 29	0.1 35	0.2 05	0.1 81	0.2 05	0.0 51	0.0 64	0.1 39	0.1 10	0.0 67	0.0 43
Income x SI	0.0 18	0.0 25	0.1 26	- 0.0 55	- 0.0 52	- 0.1 28	- 0.0 33	0.1 22	- 0.0 32	0.0 46	- 0.0 82	0.0 28	0.1 48	- 0.0 35

Gender x SI	0.0 88	0.0 31	- 0.0 56	0.0 58	0.0 37	0.1 16	- 0.0 64	0.0 96	0.0 90	- 0.0 12	0.0 39	- 0.0 87	0.0 45	0.0 18
Income x HM	0.1 79	- 0.0 20	0.1 15	- 0.1 04	- 0.1 09	- 0.1 03	0.0 62	0.0 87	0.0 33	0.1 93	0.0 19	0.0 28	0.1 88	0.0 78
Income x MOD_UPI	- 0.1 85	- 0.2 12	- 0.0 51	0.1 81	0.0 25	0.2 22	0.3 22	0.0 83	- 0.0 49	0.0 03	0.1 01	0.0 70	- 0.0 07	0.1 13
Gender x MOD_CC	0.0 34	0.0 10	0.0 48	- 0.2 60	- 0.2 59	- 0.1 40	- 0.2 81	- 0.1 38	- 0.1 03	- 0.1 49	- 0.1 55	- 0.0 95	- 0.2 23	- 0.0 54
Age x SI	- 0.1 61	- 0.0 55	- 0.0 14	0.0 81	- 0.0 40	- 0.0 11	0.1 18	0.0 97	- 0.0 07	0.0 97	0.0 74	0.0 50	0.1 05	0.0 15
Age x HM	0.1 28	- 0.0 66	0.0 76	0.0 64	- 0.0 40	0.0 31	0.1 27	0.1 60	0.0 25	0.1 34	0.0 73	- 0.0 22	0.1 37	0.1 28
Age x EE	0.0 35	- 0.0 50	- 0.0 19	0.1 17	- 0.0 05	0.0 84	0.1 37	0.0 98	- 0.0 31	0.0 48	0.0 58	- 0.0 78	0.0 95	0.0 77
Income x FC	0.1 25	- 0.0 17	0.0 81	- 0.0 60	- 0.0 86	- 0.0 76	- 0.0 19	- 0.0 57	0.0 39	0.0 44	- 0.0 60	0.1 61	0.0 02	0.0 72
Age x	-	0.0	0.0	0.0	0.1	0.1	0.1	0.0	-	0.0	0.0	-	0.0	-

MOD_UPI	0.0 80	04	77	42	46	77	65	58	0.1 27	53	57	0.0 44	01	0.1 21
Gender x VALUE_GT20	- 0.1 23	- 0.1 25	- 0.0 23	- 0.1 71	- 0.1 28	- 0.0 16	- 0.2 50	- 0.1 66	- 0.2 27	- 0.4 63	- 0.0 91	- 0.0 96	- 0.3 60	- 0.3 51
Income x MOD_BNPL_	- 0.2 18	- 0.2 90	- 0.0 82	0.0 10	- 0.1 23	0.0 12	0.1 61	- 0.0 08	- 0.0 19	0.0 27	- 0.0 53	- 0.0 41	0.0 50	0.0 68
Age x FC	0.0 23	- 0.0 27	- 0.0 30	0.0 35	- 0.0 37	0.0 36	0.1 11	0.0 21	- 0.0 35	0.0 41	0.0 66	- 0.0 03	0.0 34	0.1 11
Gender x Payment Preference	0.0 75	0.0 18	- 0.0 68	0.0 83	0.0 05	0.0 92	- 0.0 20	0.0 77	0.0 35	- 0.0 51	0.0 25	0.0 35	0.0 18	0.0 96
Income x EE	0.1 33	0.0 20	0.1 06	- 0.0 34	- 0.0 77	- 0.0 41	0.0 03	0.0 54	0.0 28	0.0 72	- 0.0 24	0.0 01	0.0 92	0.0 01
Income x Payment Preference	0.0 87	0.0 09	0.0 81	- 0.0 67	- 0.0 93	- 0.1 78	- 0.0 11	- 0.0 08	- 0.0 55	0.1 20	0.0 01	0.0 14	0.1 19	0.0 29
Gender x MOD_DW_	0.0 47	0.0 02	0.0 29	- 0.1 13	- 0.1 04	- 0.0 35	- 0.2 30	- 0.1 60	- 0.0 38	- 0.1 38	- 0.0 40	- 0.0 52	- 0.1 20	- 0.1 37
Gender x PE	- 0.0	0.0 39	- 0.0	0.0 19	0.0 07	0.1 45	- 0.0	0.0 68	0.0 91	- 0.0	0.0 09	- 0.0	0.0 65	0.0 63

	14		40				02			24		11		
Age x Trust	0.0 01	0.0 03	- 0.0 37	0.0 07	0.0 31	- 0.0 61	0.0 78	- 0.0 23	- 0.0 06	0.1 06	- 0.0 45	- 0.0 38	0.0 85	0.0 41
Gender x MOD_BNPL_	0.1 03	0.0 81	0.0 44	- 0.1 56	0.0 26	- 0.0 60	- 0.1 49	- 0.0 57	- 0.0 95	- 0.0 83	0.0 04	- 0.0 64	- 0.1 54	- 0.1 96
Gender x HM	0.0 07	0.0 14	- 0.0 58	0.0 48	0.0 51	0.1 33	0.0 01	0.0 60	0.0 91	- 0.0 60	0.0 00	0.0 33	0.0 15	0.0 39
Age x PE	0.0 02	0.0 03	0.0 23	0.1 11	0.0 10	0.0 50	0.1 28	0.1 59	0.0 30	0.0 94	0.1 31	0.0 18	0.1 40	0.0 78
Income x MOD_CC	- 0.1 84	- 0.2 34	- 0.0 60	0.2 62	0.1 04	0.2 99	0.4 17	0.0 61	- 0.0 73	- 0.0 30	0.1 52	0.0 68	- 0.0 60	0.0 32
Age x Payment Preference	0.0 72	- 0.1 04	0.0 45	0.0 88	0.0 03	- 0.0 01	0.0 99	0.0 90	- 0.0 22	0.1 00	0.1 02	- 0.0 28	0.1 02	0.0 28
Income x PE	0.1 50	0.0 21	0.1 82	- 0.0 57	- 0.0 50	- 0.0 78	- 0.0 05	0.1 24	0.0 65	0.0 90	- 0.0 11	0.0 64	0.0 93	0.0 05
Age x VALUE_GT20	- 0.0 33	0.0 49	0.0 42	- 0.1 09	- 0.0 32	- 0.0 38	0.0 92	- 0.0 16	- 0.0 68	0.2 01	- 0.0 10	- 0.0 06	- 0.0 40	- 0.1 16
Income x	-	-	-	0.0	-	0.0	0.3	0.2	-	0.0	0.0	0.0	0.0	0.1

MOD_DW_	0.1 43	0.2 01	0.0 71	00	0.0 84	67	00	49	0.0 97	64	74	00	04	07
Age x MOD_DW_	- 0.1 94	- 0.0 98	- 0.0 19	- 0.0 77	- 0.0 01	0.0 03	0.1 00	0.0 44	- 0.0 45	0.0 95	0.0 20	0.0 65	- 0.0 71	- 0.1 10
Gender x MOD_UPI	0.0 52	0.0 19	0.1 11	- 0.1 68	- 0.1 90	- 0.0 43	- 0.1 78	- 0.0 75	- 0.1 14	- 0.1 28	- 0.0 50	- 0.0 63	- 0.1 92	- 0.0 77
Age x MOD_CC	- 0.1 76	- 0.0 74	0.0 54	0.0 87	0.1 74	0.2 04	0.2 62	- 0.0 77	- 0.1 37	- 0.0 51	0.0 79	- 0.0 23	- 0.1 29	- 0.1 67
Gender x EE	- 0.0 93	0.0 65	- 0.0 79	0.0 24	0.0 63	0.0 72	0.0 11	0.1 13	0.0 35	0.0 13	- 0.0 28	- 0.0 24	0.0 00	- 0.0 13

Based on the above, we can sufficiently conclude that Fintech payment instruments and methods impact e-commerce usages differently and there lies a difference between payment method’s (BNPL, Credit Card, Digital lending & Digital Wallet) customer segmentation.

4.6.3. Research Question 3:

When this is compared for the final validated count of 201 datapoints, 173 customers have confirmed using at least one payment method. 97% of the customers have confirmed to having used at least two payment methods while 16% of the customer confirmed using all payment methods in last 12 months.

Table 44: # No of Payment Modes

#Payments	#Customer	COD	CC	DC/IB	UPI	DW	BNPL
1	5	0	0	0	5	0	0

2	16	6	7	6	9	4	0
3	39	18	26	21	37	8	7
4	40	24	27	35	39	26	9
5	46	38	43	43	44	43	19
6	27	27	27	27	27	27	27
Total	173	113	130	132	161	108	62

#Payments	#Customer	COD	CC	DC/IB	UPI	DW	BNPL
1	3%	0%	0%	0%	3%	0%	0%
2	9%	5%	5%	5%	6%	4%	0%
3	23%	16%	20%	16%	23%	7%	11%
4	23%	21%	21%	27%	24%	24%	15%
5	27%	34%	33%	33%	27%	40%	31%
6	16%	24%	21%	20%	17%	25%	44%
Total	100%	100%	100%	100%	100%	100%	100%

93% of the customers are using UPI as one of the payment methods while 36% of the customers are using BNPL.

Table 45: Type of Payment methods II

Payment	COD	CC	DC/IB	UPI	DW	BNPL
Total	65%	75%	76%	93%	62%	36%

Gender:

For the gender, Male customers are more likely to use CC, DW, and BNPL while Female customers are more likely to use DC/IB, COD, and UPI. COD is one of the payment modes for 65% (71% of the Female respondents compared to 63% of Male respondents), while for CC it is 75% (80% for

Males and 60% for females.). BNPL is one of the payment modes for only 36% of the respondents, 76% for Debit card / Internet banking, and 62% for Digital Wallet.

Table 46: Gender based Payment Method

Payment	COD	CC	DC/IB	UPI	DW	BNPL
Male	63%	80%	74%	91%	64%	37%
Female	71%	60%	82%	98%	58%	33%

Table 47: Payment modes - Gender wise

#Payments	Male	Female	Grand Total
1	3	2	5
2	13	3	16
3	27	12	39
4	30	10	40
5	35	11	46
6	20	7	27
Total	128	45	173

#Payments	Male	Female	Total
1	2.3%	4.4%	2.9%
2	10.2%	6.7%	9.2%
3	21.1%	26.7%	22.5%
4	23.4%	22.2%	23.1%
5	27.3%	24.4%	26.6%
6	15.6%	15.6%	15.6%

Total	100.0%	100.0%	100.0%
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Age:

Age also significantly affects the choice of payment mode with Gen Z customers taking the lead in using all type of payment modes with 27%, followed by 16.5% for Millennial customers. While the difference between Millennial and Gen Z customers for COD as one of the payments is not stark at ~70%, for CC customers its 65% for Gen Z, and 88% for Millennials. Also, for CC, important point is that all customer using credit card are also using at least one more digital payment mode. Expectedly BNPL is used by 47% of Gen Z customers and 34% of Millennials. Also, 99.5% of the customers using BNPL also uses three or more digital payment modes. Another point to note herein is that UPI and Digital Wallet doesn't have any age specific difference while uptake of Debit card is higher among Gen Z and Gen X & Baby boomers, as compared to Millennials.

Table 48: Payment method based on Age

#Payments	<21	21-30	31-45	46-60	60+	Total
1	2	2	1			5
2		7	6	3		16
3	2	15	21	1		39
4	1	25	14			40
5		19	25	2		46
6		15	10	1	1	27
Total	5	83	77	7	1	173

Table 49: Payment Method based on Age II

Age	Total	COD	CC	DC/IB	UPI	DW	BNPL
<21	5	1	1	2	5	2	1
21-30	83	56	55	69	79	51	36
31-45	77	51	70	54	71	49	22
46-60	7	4	3	6	5	5	2
60+	1	1	1	1	1	1	1
Total	173	113	130	132	161	108	62

Table 50: Payment Method based on Age III

Age	Total	COD	CC	DC/IB	UPI	DW	BNPL
<21	5	20%	20%	40%	100%	40%	20%
21-30	83	67%	66%	83%	95%	61%	43%
31-45	77	66%	91%	70%	92%	64%	29%
46-60	7	57%	43%	86%	71%	71%	29%
60+	1	100%	100%	100%	100%	100%	100%
Total	173	65%	75%	76%	93%	62%	36%

Income:

It can be seen that there is a strong correlation between Payment method used and Income. With increase in income, the uptake on CC increases with 96% of the 25-50L income customers using Credit Card. The case is reversed for BNPL & Debit Card / Internet Banking with the uptake decreasing with increase in Income. UPI uptake was very high and similar across income segment.

Table 51: Payment Method moderated by Income

Income	Total	COD	CC	DC/IB	UPI	DW	BNPL
<5L	59	54%	58%	80%	95%	53%	47%
5-10	43	74%	77%	79%	88%	63%	35%
10-25	39	64%	85%	77%	95%	72%	31%
25-50	28	75%	96%	61%	93%	68%	21%
50+	4	75%	75%	100%	100%	75%	25%

Additionally, BI2 and BI6 are strongly correlated with Frequency of purchase of CC suggesting that the customers with higher probability to switch to a different payment mode due to availability, or offers and discounts are more likely to have higher frequency of purchases. Based on the above details, RQ3 is validated.

As per customer perception, COD and Debit Card/ Internet banking are less affected by WOM, compared to Digital Wallet and BNPL.

4.7. Summary

The above chapter through an objective based analysis based on Hierarchical clustering along with PLS SEM was able to validate / reject / redact all the thesis hypothesis. For PLS SEM, models' validity, reliability, collinearity, predictability, and strength is duly checked. The chapter also explained the validation of the three research questions in details.

CHAPTER 5: CONCLUSION AND DISCUSSIONS

5. DISCUSSION AND IMPLICATIONS

The above research has extensively analysed and uniquely proposed a model for showcasing the role and moderating effect of payment methods in E-commerce purchases in Indian context for the first time. Additionally, the study through an extensive literature review of various communication theories like IDT, DOI, RFM and customer purchase lifecycle proposes a novel Attributes of Tech (AOT) theory comprising of Acceptability, Accessibility, Adaptability, Affordability, Applicability, and Availability. The author also proposed another driver for purchase intention as External Factor & Communication (EFC) encompassing the environmental factors like geopolitical factors, events, policies, and communication factors (Intra, interpersonal, and external). These constructs along with Behavioural factor (Pricing), and proposed payment preference (PP) is used to highlight the impact of payment method on the customer's E-commerce purchase in intentions using a modified UTAUT2 model (Combination of UTAUT2, AOT theory, RFM, Behavioural segmentation, and communication theory). This is also analysed to understand the impact of various constructs on the frequency of purchases using different payment methods. For this, the methodology used is RFM modelling, followed by K-mean clustering for purchase type, and value clustering which is validated by Hierarchical clustering. This also results in identification of significant purchase type indicators using various payment methods. These indicators along with the above discussed construct is used to create the STATE (SBE, Type of Purchase, AOT, Type of Customer, and EFC) model for signifying the importance of payment method on the E-commerce purchase. This model is validated using PLS-SEM method and insights are reported.

5.1. Theoretic Implications

Post extensive literature review, Author has created unique models of AOT theory, and the STATE model which is a novice approach to interpret the impact of various factors including Behavioural, Demographic, External, Perspective, and Technological indicators. This research is also a first in Indian context to validate the significance of payment methods on the E-commerce purchases. This research adds to the literature by differentiating the purchase pattern of customers for various payment modes. The study supports through a significant effect of TrustxSBE (0.331) and PPxTrust (0.467), the previous studies by L. Alfansi and M. I. Daulay (2021), Lee (2006), Lin & Wang (2010), and Nguyen (2016) stating that Trust is a major factor for E-commerce purchases through various payment methods. For the BNPL customer segmentation, while Backer (2022) suggested that % of Male uses are higher than Female, the current study identifies that % of Female BNPL users (46%) out of total Female users are higher than same for Male users (40%). The study correlates that Gen Z are the biggest age segment with 47% of Gen Z at least using BNPL compared to only 34% for Millennials. This also corroborates with the Payment Journal (2021) which suggest that BNPL customers are mainly Gen Z, at the same time contradicting the RFI (2022) findings suggesting BNPL to be Gen X and Baby Boomers in India. Additionally, contrary to Bain (2021), the current research didn't find any major significant difference between Millennial and Gen Z based on Value of purchases. Additionally, the current research identifies that BNPL purchases are affected by external factors and communications including Government Policies, Geopolitical Factors, WOM, Reviews, and advertisements. For Credit Card, the research validates the previous findings by Fiori et al (2014) suggesting, offers, discounts, and rewards has a significant positive effect on the choice of payment method as CC. Additionally, the research also confirms the Khare et al. (2021) research suggesting that Age, Gender, and Income affect the user with Millennial are more likely to use credit card v/s Gen Z (88% v/s 65%), Male users are more likely to use it compare to Female customers (77% v/s 65%) and higher usage of credit card is expected with increase in income. Another important factor

shows that with increase in income (83% for >10L vs 70% for <10L), age (millennials~80% v/s Gen Z~72%), and Gender (92% for Male vs 78% for Female), the customer perception towards the role of rewards and discounts increases for credit card customers. The trend is similar and stronger for UPI customers which indicates a strong impact of rewards and discounts for UPI customers as well. The biggest significance of this study is validated STATE model for understanding the customer preference of choice of payment when doing an e-commerce purchase:

- 37.1.1 AOT (Attribute of Tech) indicators (UI/CX, 1-click Payments, Widespread availability, Merchant acceptability, High Security, Ease of Payment) positively affects the payment preference of the customer as well as indirect effect on the customer E-commerce behaviour intentions
- 37.1.2 Pricing (Rewards and Discounts) has a significant impact on customer E-commerce purchase intention and payment preference
- 37.1.3 EFC-2 (Government Policies and Geopolitical Factors) has significant impact on customer payment preference and total indirect effect on customer behaviour intentions.
- 37.1.4 EFC-1 doesn't have a significant role on payment preference and customer behaviour intentions but do affect in actual purchases using choice of payment method.
- 37.1.5 Demographics (Age, Income, and Gender) moderates customer intention for E-commerce purchases through different payment modes.
- 37.1.6 Payment preference has a significant impact on customer purchase intentions through E-commerce payments.

37.2 Implementable Insights

- 37.2.1 Payment parameters i.e. Discounts and rewards have a significant impact on customer purchase intentions
- 37.2.2 Customer choice of payment method is moderated by generational segmentation, Income and Gender

- 37.2.3 Customer choice of payment method is affected by Government Policy and Geopolitical factors
- 37.2.4 Various Technology factors like Merchant Acceptability of payment method, Security, UI/CX, wider availability of payment modes, 1-click payment facility, and ease of payment affect customer intention to use digital payments and choice of payment method.
- 37.2.5 External communications like Advertisements, WOM, and Reviews affect customer choice of payment method but doesn't affect customer purchase intention using digital payment modes.
- 37.2.6 Trust is a strong factor in customer purchase intentions using digital payment mode along with PE, EE, SI, and FC. Hedonic motivation impacts customer purchase intention when moderated by age.
- 37.2.7 Type of purchase and value of purchase affect customer frequency of purchase using a specific payment method.

5.2. Strengths and Weaknesses of the Study

5.2.1. Strengths

5.2.1.1 This is a unique study to understand the impact of customer segmentation of BNPL, Credit Card & Digital Lending in Indian Market

5.2.1.2 As per the extensive research on the subject, this is the first academic study to compare the segmentations between various payment & credit products anywhere in the world

5.2.1.3 This study creates a model to identify the right customer segmentation for payment methods and factors affecting choice of payment methods. Considering the multiple commercial challenges faced by Payments companies, this research will be able to identify target & niche segments for the product

5.2.1.4 This research has huge academic and commercial significance for Credit Card & Digital lending companies as it checks the impact of other products like BNPL, UPI & Digital Wallet.

5.2.2 Weakness & Limitation of Study

5.2.2.1 The research sampling is majorly skewed towards urban salaried income groups and the research doesn't have sufficient feedback of Tier II & Rural segments. This may lead to skewed feedback for financial inclusion norms.

5.2.2.2 The study subjects are limited to India and there is a possibility of geographical divergence in customer behaviour with the similar attributes and hence further research is required across multiple geographies to revalidate the results

5.2.2.3 The study was done on a limited set of ~400 customers to represent the true sample out of which 201 samples were fully validated and used for final analysis. While the method used allows for working with smaller samples and the data is revalidated using PLSpredict and IMPA, a wider coverage may result in slightly varying result.

5.3 Research Significance

This research has created a unique model framework for customer segmentation difference between various payment instruments (BNPL, Credit Card, Personal Loan & Digital lending) in Indian Market. This research has also worked to identify if there is a significant difference between these products and if yes, what is the extend of difference. With this, the current research has worked for demarcated segments for various products.

The 2nd significance of this research is that it helps to identify the potentially optimal customer segmentation for various payment products and identify new markets & segments to ensure long term growth within the Indian market and extend the learnings to other geographies through future validation of model.

The 3rd significance of this research is to understand the impact of payment instruments on E-commerce consumer behaviour and also on the customer segmentation in India market. This research has worked to understand this moderating effect of payment instruments on customer segmentation and expects to create one of the first such study in Indian market.

5.4 Research

The research has worked to create an initial framework for customer segmentation of payment model and opens up a new area of research on this topic. As the current research has redacted the medium of payment, various other variables due to smaller sample size, future research can work to identify the significance of these. Additionally, the researchers can also cross validate the outcome of this research with other geographies or for many smaller micro markets. The researchers in future can also create specific weightage for each of the STATE pillars and create a single expression for payment mode classification.

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Referencing

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APPENDICES

Appendix 1: Questionnaire

Attached as PDF

Questionnaire Variable Construct Details

Table 52: Variable construct

Original Variables	Original Scale	Final Variable	Final Scale	Variables Used / Discarded from Model	Model Construct	Scale definition
Gender	Nominal	Gender	Binary	Used	Demographics	Control
Age	Ordinal	Age	Ordinal	Used	Demographics	Control
City	Nominal	Geography	Nominal	Discarded due to model FIT	Geographics	Control
Income	Ordinal	Income	Ordinal	Used	Demographics	Control

Occupation	No min al	Occupa tion	No mi nal	Discarded due to model FIT	Demo graph ics	Contro l
Frequency Purchase_Ecom	ordi nal	Purfreq _Ecom	ord ina l	Discarded due to model FIT	Beha viour al	RFM
Education	ordi nal	Educati on	ord ina l	Discarded due to model FIT	Demo graph ics	Contro l
I am more likely to dump the cart if payment methods are too cumbersome.	like rt	BI7	lik ert	Discarded due to model FIT	SBE	Venkat esh et al. (2012)
Digital payment methods are easy to learn and use for online shopping	like rt	EE2	lik ert	Used	SBE	Venkat esh et al. (2012)
I had a positive experience using a digital payment method when shopping online	like rt	BI1	lik ert	Discarded due to model FIT	SBE	Venkat esh et al. (2012)
I find Digital Payments terms & condition for online purchases to be clear & transparent	like rt	FC5	lik ert	Used	SBE	Venkat esh et al. (2012)

My Knowledge of Digital Payments has helped me in using new E-commerce apps	like rt	FC1	lik ert	Used	SBE	Venkat esh et al. (2012)
I am able to take help from others to use Digital Payments	like rt	FC2	lik ert	Discarded due to model FIT	SBE	Venkat esh et al. (2012)
I expect E-commerce site / App to have my preferred payment method	like rt	PP4	lik ert	Used	Paym ent Prefer ence	Scale Develo pment
I will switch purchases from my regular website if it stops offering my preferred payment method	like rt	BI3	lik ert	Used	SBE	Scale Develo pment
I mostly use one specific Digital payment method for my online purchase	like rt	PP1	lik ert	Used	Paym ent Prefer ence	Scale Develo pment
The fun of earning rewards points / discounts on payments makes the online shopping more exciting..	like rt	HM1	lik ert	Used	SBE	Venkat esh et al. (2012)
I find shopping online using digital payment to be fun and Enjoyable	like rt	HM2	lik ert	Used	SBE	Venkat esh et

						al. (2012)
I believe that not having a credit card limits online purchases capacity	like rt	PP2	lik ert	Used	Paym ent Prefer ence	Scale Develo pment
Having multiple payment options with good credit limit & EMI gives me confidence to purchase online	like rt	PP3	lik ert	Used	Paym ent Prefer ence	Scale Develo pment
I find Digital payments convenient for tracking my E-commerce purchases	like rt	PE1	lik ert	Used	SBE	Venkat esh et al. (2012)
One-click Payment has made my E-commerce purchases convenient and faster	like rt	EE3	lik ert	Used	SBE	Venkat esh et al. (2012)
I will not buy from secured E-comm websites if it stops providing secure payment methods.	like rt	BI6	lik ert	Used	SBE	Venkat esh et al. (2012)
I am likely to cancel the purchase at checkout if the payment method looks suspicious	like rt	BI5	lik ert	Used	SBE	Venkat esh et

						al. (2012)
Digital payment authentication & security helps in reducing E-commerce risk of fraudulent transactions	like rt	FC4	lik ert	Discarded due to model FIT	SBE	Venkat esh et al. (2012)
I will switch to a rival E-comm site /app if it offers me good discounts on Digital payment methods	like rt	BI2	lik ert	Used	SBE	Venkat esh et al. (2012)
I get more discounts and offers on E-commerce website using Digital Payment	like rt	PE3	lik ert	Used	SBE	Venkat esh et al. (2012)
My Friends / Family members are saving a lot of money by using Digital payments to make online purchase	like rt	SI1	lik ert	Used	SBE	Venkat esh et al. (2012)
My Friends / Family Members think that I will save money & time by using Digital payments to make online purchase	like rt	Si2	lik ert	Used	SBE	Venkat esh et al. (2012)
I am more likely to trust a new E-commerce website if it offers me my trusted payment options	like rt	T1	lik ert	Used	SBE	Venkat esh et

						al. (2012)
It will decrease my trust in an E-commerce site if it asks me to pay through unknown payment method	like rt	T2	lik ert	Used	SBE	Venkat esh et al. (2012)
Features Affecting Payments Mode - Rewards / Loyalty Points	like rt	Reward s	lik ert	Used	Pricin g	Scale Develo pment
Features Affecting Payments Mode - Discounts / Offers	like rt	Discou nt	lik ert	Used	Pricin g	Scale Develo pment
Features Affecting Payments Mode - Fees / Charges	like rt	Fees_c harges	lik ert	Discarded due to model FIT	Pricin g	Scale Develo pment
Features Affecting Payments Mode - One Click Payment	like rt	1clickP ayment	lik ert	Used	AOT	Scale Develo pment
Features Affecting Payments Mode - High Security	like rt	High_s ecurity	lik ert	Used	AOT	Scale Develo pment
Features Affecting Payments Mode - EMI Option	like rt	EMI_o ption	lik ert	Discarded due to model FIT	AOT	Scale Develo pment

Features Affecting Payments Mode - Reviews / Ratings	like rt	Review s	lik ert	Used	EFC- 1	Scale Develo pment
Features Affecting Payments Mode – WOM	like rt	WOM	lik ert	Used	EFC- 1	Scale Develo pment
Features Affecting Payments Mode - Ease of Payment	like rt	Ease_p ayment	lik ert	Used	AOT	Scale Develo pment
Features Affecting Payments Mode - Widespread availability	like rt	Widesp read_av ailabilit y	lik ert	Used	AOT	Scale Develo pment
Features Affecting Payments Mode - UI & Customer Experience	like rt	UI_CX	lik ert	Used	AOT	Scale Develo pment
Features Affecting Payments Mode - Sales Promotions / Advertisements	like rt	Promo_ Advert	lik ert	Used	EFC- 1	Scale Develo pment
Features Affecting Payments Mode - Government Policy	like rt	Govern _Policy	lik ert	Used	EFC- 2	Scale Develo pment
Features Affecting Payments Mode - Geopolitical Factors	like rt	Geopoli tical	lik ert	Used	EFC- 2	Scale Develo pment

Features Affecting Payments Mode - Refund requirement	like rt	Refund _ref	lik ert	Discarded due to model FIT	AOT	Scale Develo pment
Features Affecting Payments Mode - Merchant Acceptability	like rt	Merc_ Acce	lik ert	Used	AOT	Scale Develo pment
No of Online Purchases in the last 12 Months – COD	ordi nal	Freq_T OP1	ordi nal	Used	Freq_ COD	Scale Develo pment
No of Online Purchases in the last 12 Months - Credit Card	ordi nal	Freq_T OP2	ordi nal	Used	Freq_ CC	Scale Develo pment
No of Online Purchases in the last 12 Months - Debit Card / Internet Banking	ordi nal	Freq_T OP3	ordi nal	Used	Freq_ DCIB	Scale Develo pment
No of Online Purchases in the last 12 Months – UPI	ordi nal	Freq_T OP4	ordi nal	Used	Freq_ UPI	Scale Develo pment
No of Online Purchases in the last 12 Months - Digital Wallets	ordi nal	Freq_T OP5	ordi nal	Used	Freq_ DW	Scale Develo pment
No of Online Purchases in the last 12 Months - Pay Later options	ordi nal	Freq_T OP6	ordi nal	Used	Freq_ BNP L	Scale Develo pment

Medium of Purchase - COD	No min al	Mediu m_TOP 1	No mi nal	Discarded	Medi um_T OP1	Scale Develo pment
Medium of Purchase - Credit Card	No min al	Mediu m_TOP 2	No mi nal	Discarded	Medi um_T OP2	Scale Develo pment
Medium of Purchase - Debit Card / Internet Banking	No min al	Mediu m_TOP 3	No mi nal	Discarded	Medi um_T OP3	Scale Develo pment
Medium of Purchase - UPI	No min al	Mediu m_TOP 4	No mi nal	Discarded	Medi um_T OP4	Scale Develo pment
Medium of Purchase - Digital Wallet	No min al	Mediu m_TOP 5	No mi nal	Discarded	Medi um_T OP5	Scale Develo pment
Medium of Purchase - Pay Later App	No min al	Mediu m_TOP 6	No mi nal	Discarded	Medi um_T OP6	Scale Develo pment
Preferred Payment Method - COD	No min al	MOD_ COD_E LEC	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CO D	Scale Develo pment
Preferred Payment Method - COD	No min al	MOD_ COD_ GR	Bi nar y	Discarded based on K-Mean &	MOD _CO D	Scale Develo pment

				Heirarchical clustering		
Preferred Payment Method - COD	No min al	MOD_ COD_F D	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CO D	Scale Develo pment
Preferred Payment Method - COD	No min al	MOD_ COD_T RVL	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CO D	Scale Develo pment
Preferred Payment Method - COD	No min al	MOD_ COD_F ashion	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CO D	Scale Develo pment
Preferred Payment Method - COD	No min al	MOD_ COD_ Others	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CO D	Scale Develo pment
Preferred Payment Method - Credit Card	No min al	MOD_ CC_EL EC	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CC	Scale Develo pment
Preferred Payment Method - Credit Card	No min al	MOD_ CC_GR	Bi nar y	Used	MOD _CC	Scale Develo pment

Preferred Payment Method - Credit Card	No min al	MOD_ CC_FD	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CC	Scale Develo pment
Preferred Payment Method - Credit Card	No min al	MOD_ CC_TR VL	Bi nar y	Used	MOD _CC	Scale Develo pment
Preferred Payment Method - Credit Card	No min al	MOD_ CC_FA SHION	Bi nar y	Used	MOD _CC	Scale Develo pment
Preferred Payment Method - Credit Card	No min al	MOD_ CC_Ot hers	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _CC	Scale Develo pment
Preferred Payment Method - Debit Card / Internet Banking	No min al	MOD_ DCIB_ ELEC	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DCI B	Scale Develo pment
Preferred Payment Method - Debit Card / Internet Banking	No min al	MOD_ DCIB_ GR	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DCI B	Scale Develo pment
Preferred Payment Method - Debit Card / Internet Banking	No min al	MOD_ DCIB_ FD	Bi nar y	Discarded based on K-Mean &	MOD _DCI B	Scale Develo pment

				Heirarchical clustering		
Preferred Payment Method - Debit Card / Internet Banking	No min al	MOD_ DCIB_ TRVL	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DCI B	Scale Develo pment
Preferred Payment Method - Debit Card / Internet Banking	No min al	MOD_ DCIB_ FASHI OM	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DCI B	Scale Develo pment
Preferred Payment Method - Debit Card / Internet Banking	No min al	MOD_ DCIB_ Others	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DCI B	Scale Develo pment
Preferred Payment Method - UPI	No min al	MOD_ UPI_E LEC	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _UPI	Scale Develo pment
Preferred Payment Method - UPI	No min al	MOD_ UPI_G R	Bi nar y	Used	MOD _UPI	Scale Develo pment
Preferred Payment Method - UPI	No min al	MOD_ UPI_F D	Bi nar y	Used	MOD _UPI	Scale Develo pment

Preferred Payment Method - UPI	No min al	MOD_ UPI_T RVL	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _UPI	Scale Develo pment
Preferred Payment Method - UPI	No min al	MOD_ UPI_F ASHIO N	Bi nar y	Used	MOD _UPI	Scale Develo pment
Preferred Payment Method - UPI	No min al	MOD_ UPI_Ot hers	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _UPI	Scale Develo pment
Preferred Payment Method - Digital Wallets	No min al	MOD_ DW_E LEC	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DW	Scale Develo pment
Preferred Payment Method - Digital Wallets	No min al	MOD_ DW_G R	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DW	Scale Develo pment
Preferred Payment Method - Digital Wallets	No min al	MOD_ DW_F D	Bi nar y	Used	MOD _DW	Scale Develo pment

Preferred Payment Method - Digital Wallets	No min al	MOD_ DW_T RVL	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DW	Scale Develo pment
Preferred Payment Method - Digital Wallets	No min al	MOD_ DW_Fa shion	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DW	Scale Develo pment
Preferred Payment Method - Digital Wallets	No min al	MOD_ DW_Ot hers	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DW	Scale Develo pment
Preferred Payment Method - Pay Later Apps	No min al	MOD_ BNPL_ ELEC	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _BNP L	Scale Develo pment
Preferred Payment Method - Pay Later Apps	No min al	MOD_ BNPL_ GR	Bi nar y	Used	MOD _BNP L	Scale Develo pment
Preferred Payment Method - Pay Later Apps	No min al	MOD_ BNPL_ FD	Bi nar y	Used	MOD _BNP L	Scale Develo pment
Preferred Payment Method - Pay Later Apps	No min al	MOD_ BNPL_ TRVL	Bi nar y	Used	MOD _BNP L	Scale Develo pment

Preferred Payment Method - Pay Later Apps	No min al	MOD_ BNPL_ Fashion	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _BNP L	Scale Develo pment
Preferred Payment Method - Pay Later Apps	No min al	MOD_ BNPL_ Others	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _BNP L	Scale Develo pment
Value of purchase in INR - COD	ordi nal	VALU E_COD _LT100	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	VAL UE_C OD	Scale Develo pment
Value of purchase in INR - COD	ordi nal	VALU E_COD _100_1 K	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	VAL UE_C OD	Scale Develo pment
Value of purchase in INR - COD	ordi nal	VALU E_COD _1K_20 K	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	VAL UE_C OD	Scale Develo pment
Value of purchase in INR - COD	ordi nal	VALU E_COD _GT20 K	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	VAL UE_C OD	Scale Develo pment

Value of purchase in INR - Credit Card	ordinal	VALUE_CC_LT100	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_CC	Scale Development
Value of purchase in INR - Credit Card	ordinal	VALUE_CC_100_1K	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_CC	Scale Development
Value of purchase in INR - Credit Card	ordinal	VALUE_CC_1K_20K	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_CC	Scale Development
Value of purchase in INR - Credit Card	ordinal	VALUE_CC_GT20K	Binary	Used	MOD_CC	Scale Development
Value of purchase in INR - Debit Card / Internet Banking	ordinal	VALUE_DCI_B_LT100	Binary	Discarded based on K-Mean & Heirarchical clustering	MOD_DCI_B	Scale Development
Value of purchase in INR - Debit Card / Internet Banking	ordinal	VALUE_DCI_B_100_1K	Binary	Discarded based on K-Mean & Heirarchical clustering	MOD_DCI_B	Scale Development

Value of purchase in INR - Debit Card / Internet Banking	ordi nal	VALU E_DCI B_1K_ 20K	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	MOD _DCI B	Scale Develo pment
Value of purchase in INR - Debit Card / Internet Banking	ordi nal	VALU E_DCI B_GT2 0K	Bi nar y	Used	VAL UE_ GT20 K	Scale Develo pment
Value of purchase in INR - UPI	ordi nal	VALU E_UPI_ LT100	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	VAL UE_ UPI	Scale Develo pment
Value of purchase in INR - UPI	ordi nal	VALU E_UPI_ 100_1K	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	VAL UE_ UPI	Scale Develo pment
Value of purchase in INR - UPI	ordi nal	VALU E_UPI_ 1K_20 K	Bi nar y	Discarded based on K-Mean & Heirarchical clustering	VAL UE_ UPI	Scale Develo pment
Value of purchase in INR - UPI	ordi nal	VALU E_UPI_ GT20K	Bi nar y	Used	VAL UE_ GT20 K	Scale Develo pment

Value of purchase in INR - Digital Wallets	ordinal	VALUE_DW_LT100	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_DW	Scale Development
Value of purchase in INR - Digital Wallets	ordinal	VALUE_DW_100_1K	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_DW	Scale Development
Value of purchase in INR - Digital Wallets	ordinal	VALUE_DW_1K_20K	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_DW	Scale Development
Value of purchase in INR - Digital Wallets	ordinal	VALUE_DW_GT20K	Binary	Used	VALUE_GT20K	Scale Development
Value of purchase in INR - Pay Later options	ordinal	VALUE_BNP_LT100	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_BNP	Scale Development
Value of purchase in INR - Pay Later options	ordinal	VALUE_BNP_100_1K	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_BNP	Scale Development

Value of purchase in INR - Pay Later options	ordinal	VALUE_BNP_L_1K_20K	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_BNP_L_1K_20K	Scale Development
Value of purchase in INR - Pay Later options	ordinal	VALUE_BNP_L_GT2_0K	Binary	Discarded based on K-Mean & Heirarchical clustering	VALUE_BNP_L_GT2_0K	Scale Development

Appendix 2: Scale modification from nominal to Binary

Original Scale:

Table 53: Scale Modification

Original Variable	Multi Answer Nominal Scale	Values
Preferred Payment Method - COD	Electronics, Grocery, Food Delivery, Travel, Fashion, Others	1-6
Preferred Payment Method - Credit Card	Electronics, Grocery, Food Delivery, Travel, Fashion, Others	1-6
Preferred Payment Method - Debit Card / Internet Banking	Electronics, Grocery, Food Delivery, Travel, Fashion, Others	1-6
Preferred Payment Method - UPI	Electronics, Grocery, Food Delivery, Travel, Fashion, Others	1-6
Preferred Payment Method - Digital Wallets	Electronics, Grocery, Food Delivery, Travel, Fashion, Others	1-6
Preferred Payment Method - Pay Later Apps	Electronics, Grocery, Food Delivery, Travel, Fashion, Others	1-6

Value of purchase in INR - COD	<100,100-1000,1000-20K,20K+	1-4
Value of purchase in INR - Credit Card	<100,100-1000,1000-20K,20K+	1-4
Value of purchase in INR - Debit Card / Internet Banking	<100,100-1000,1000-20K,20K+	1-4
Value of purchase in INR - UPI	<100,100-1000,1000-20K,20K+	1-4
Value of purchase in INR - Digital Wallets	<100,100-1000,1000-20K,20K+	1-4
Value of purchase in INR - Pay Later options	<100,100-1000,1000-20K,20K+	1-4

Update Scale:

Table 54: Update Scale II

Original Variable	New Variable	Category	Value if Yes
Preferred Payment Method - COD	MOD_COD_ELEC	Electronics	1
Preferred Payment Method - COD	MOD_COD_GR	Grocery	1
Preferred Payment Method - COD	MOD_COD_FD	Food Delivery	1
Preferred Payment Method - COD	MOD_COD_TRVL	Travel	1
Preferred Payment Method - COD	MOD_COD_Fashio n	Fashion	1
Preferred Payment Method - COD	MOD_COD_Others	Others	1
Preferred Payment Method - Credit Card	MOD_CC_ELEC	Electronics	1
Preferred Payment Method - Credit Card	MOD_CC_GR	Grocery	1
Preferred Payment Method - Credit Card	MOD_CC_FD	Food Delivery	1
Preferred Payment Method - Credit Card	MOD_CC_TRVL	Travel	1

	MOD_CC_FASHIO		
Preferred Payment Method - Credit Card	N	Fashion	1
Preferred Payment Method - Credit Card	MOD_CC_Others	Others	1
Preferred Payment Method - Debit Card / Internet Banking	MOD_DCIB_ELEC	Electronics	1
Preferred Payment Method - Debit Card / Internet Banking	MOD_DCIB_GR	Grocery	1
Preferred Payment Method - Debit Card / Internet Banking	MOD_DCIB_FD	Food Delivery	1
Preferred Payment Method - Debit Card / Internet Banking	MOD_DCIB_TRVL	Travel	1
Preferred Payment Method - Debit Card / Internet Banking	MOD_DCIB_FASH IOM	Fashion	1
Preferred Payment Method - Debit Card / Internet Banking	MOD_DCIB_Others	Others	1
Preferred Payment Method - UPI	MOD_UPI_ELEC	Electronics	1
Preferred Payment Method - UPI	MOD_UPI_GR	Grocery	1
Preferred Payment Method - UPI	MOD_UPI_FD	Food Delivery	1
Preferred Payment Method - UPI	MOD_UPI_TRVL	Travel	1
Preferred Payment Method - UPI	MOD_UPI_FASHI ON	Fashion	1
Preferred Payment Method - UPI	MOD_UPI_Others	Others	1
Preferred Payment Method - Digital Wallets	MOD_DW_ELEC	Electronics	1
Preferred Payment Method - Digital Wallets	MOD_DW_GR	Grocery	1

Preferred Payment Method - Digital Wallets	MOD_DW_FD	Food Delivery	1
Preferred Payment Method - Digital Wallets	MOD_DW_TRVL	Travel	1
Preferred Payment Method - Digital Wallets	MOD_DW_Fashion	Fashion	1
Preferred Payment Method - Digital Wallets	MOD_DW_Others	Others	1
Preferred Payment Method - Pay Later Apps	MOD_BNPL_ELEC	Electronics	1
Preferred Payment Method - Pay Later Apps	MOD_BNPL_GR	Grocery	1
Preferred Payment Method - Pay Later Apps	MOD_BNPL_FD	Food Delivery	1
Preferred Payment Method - Pay Later Apps	MOD_BNPL_TRV L	Travel	1
Preferred Payment Method - Pay Later Apps	MOD_BNPL_Fashi on	Fashion	1
Preferred Payment Method - Pay Later Apps	MOD_BNPL_Other s	Others	1
Value of purchase in INR - COD	VALUE_COD_LT1 00	<100	1
Value of purchase in INR - COD	VALUE_COD_100 _1K	100-1000	1
Value of purchase in INR - COD	VALUE_COD_1K_ 20K	1000-20K	1
Value of purchase in INR - COD	VALUE_COD_GT2 0K	20K+	1
Value of purchase in INR - Credit Card	VALUE_CC_LT10 0	<100	1

Value of purchase in INR - Credit Card	VALUE_CC_100_1 K	100-1000	1
Value of purchase in INR - Credit Card	VALUE_CC_1K_2 0K	1000-20K	1
Value of purchase in INR - Credit Card	VALUE_CC_GT20 K	20K+	1
Value of purchase in INR - Debit Card / Internet Banking	VALUE_DCIB_LT 100	<100	1
Value of purchase in INR - Debit Card / Internet Banking	VALUE_DCIB_100 _1K	100-1000	1
Value of purchase in INR - Debit Card / Internet Banking	VALUE_DCIB_1K _20K	1000-20K	1
Value of purchase in INR - Debit Card / Internet Banking	VALUE_DCIB_GT 20K	20K+	1
Value of purchase in INR - UPI	VALUE_UPI_LT10 0	<100	1
Value of purchase in INR - UPI	VALUE_UPI_100_ 1K	100-1000	1
Value of purchase in INR - UPI	VALUE_UPI_1K_2 0K	1000-20K	1
Value of purchase in INR - UPI	VALUE_UPI_GT20 K	20K+	1
Value of purchase in INR - Digital Wallets	VALUE_DW_LT10 0	<100	1

Value of purchase in INR - Digital Wallets	VALUE_DW_100_ 1K	100-1000	1
Value of purchase in INR - Digital Wallets	VALUE_DW_1K_2 0K	1000-20K	1
Value of purchase in INR - Digital Wallets	VALUE_DW_GT20 K	20K+	1
Value of purchase in INR - Pay Later options	VALUE_BNPL_LT 100	<100	1
Value of purchase in INR - Pay Later options	VALUE_BNPL_10 0_1K	100-1000	1
Value of purchase in INR - Pay Later options	VALUE_BNPL_1K _20K	1000-20K	1
Value of purchase in INR - Pay Later options	VALUE_BNPL_GT 20K	20K+	1

Likert Scale:

Table 55: Likert Scale

Likert Scale	Value Taken
Strongly Agree	1
Mostly Agree	2
Somewhat Agree	3
Neutral	4
Somewhat Disagree	5
Mostly Disagree	6
Strongly Disagree	7

Appendix 3: Output file detailing the variable wise values of Frequency, Missing value, Mean, Median, Std. Deviation, Kurtosis, Skewness

Table 56: Outer Variable Analysis

Variables	Valid	Missing	Mean	Median	Std. Deviation	Variance	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	25	50	75
Gender	302	0	1.31	1	0.462	0.214	0.836	0.14	-1.309	0.28	1	1	2
Age	302	0	2.43	2	0.632	0.399	0.371	0.14	0.417	0.28	2	2	3
Geography	302	0	1.08	1	0.266	0.071	3.212	0.14	8.371	0.28	1	1	1
Income	302	0	2.08	2	1.183	1.398	0.725	0.14	-0.682	0.28	1	2	3
Occupation	302	0	1.15	1	0.516	0.267	4.566	0.14	24.976	0.28	1	1	1
Purfreq_Ecom	302	0	2.44	2	1.56	2.433	0.653	0.14	-1.134	0.28	1	2	4

Education	30 2	0	2.8 7	3	0.659	0.43 4	- 0.483	0.14	0.71 3	0.28	3	3	3
Features1	27 5	27	1.7 9	1	1.282	1.64 4	1.925	0.147	3.76 3	0.29 3	1	1	2
Features2	27 6	26	1.7 4	1	1.097	1.20 4	1.696	0.147	2.84	0.29 2	1	1	2
Features3	26 8	34	2.0 9	1	1.454	2.11 5	1.434	0.149	1.62 6	0.29 7	1	1	3
Features4	27 2	30	2.0 2	1	1.322	1.74 9	1.3	0.148	1.26 7	0.29 4	1	1	3
Features5	27 1	31	1.7 3	1	1.164	1.35 5	1.711	0.148	2.51 8	0.29 5	1	1	2
Features6	27 1	31	2.0 6	2	1.358	1.84 4	1.307	0.148	1.20 5	0.29 5	1	2	3
Features7	27 0	32	2.0 3	1.5	1.347	1.81 3	1.409	0.148	1.66 1	0.29 5	1	1 5	3
Features8	26 5	37	2.3 2	2	1.305	1.70 4	0.686	0.15	- 0.31 6	0.29 8	1	2	3
Features9	26 8	34	1.8 4	1	1.192	1.42 1	1.603	0.149	2.15 8	0.29 7	1	1	2
Features10	27 1	31	2 2	2	1.24	1.53 7	1.215	0.148	1.15 6	0.29 5	1	2	3

Features11	26 6	36	1.9 8	2	1.213	1.47 1	1.092	0.149	0.43 8	0.29 8	1	2	3
Features12	27 0	32	2.1 5	2	1.283	1.64 6	1.043	0.148	0.69 6	0.29 5	1	2	3
Features13	27 1	31	2.1 3	2	1.309	1.71 3	1.057	0.148	0.71	0.29 5	1	2	3
Features14	27 1	31	2.2 7	2	1.335	1.78 3	0.747	0.148	- 0.31 2	0.29 5	1	2	3
Features15	27 2	30	1.7 8	1	1.111	1.23 5	1.469	0.148	1.82 3	0.29 4	1	1	2
Features16	27 2	30	1.8 8	1	1.143	1.30 7	1.247	0.148	1.02 2	0.29 4	1	1	2
Freq_TOP1	26 4	38	1.9 1	2	0.736	0.54 2	0.151	0.15	- 1.14	0.29 9	1	2	2
Freq_TOP2	26 7	35	2.0 7	2	0.811	0.65 7	- 0.124	0.149	- 1.46 7	0.29 7	1	2	3
Freq_TOP3	26 5	37	2.0 2	2	0.773	0.59 8	- 0.039	0.15	- 1.32 3	0.29 8	1	2	3
Freq_TOP4	26 7	35	2.3 7	3	0.736	0.54 1	- 0.702	0.149	- 0.84 3	0.29 7	2	3	3

Freq_TOP5	26 6	36	1.8 3	2	0.757	0.57 4	0.3	0.149	- 1.20 3	0.29 8	1	2	2
Freq_TOP6	26 5	37	1.5 5	1	0.738	0.54 4	0.949	0.15	- 0.53 7	0.29 8	1	1	2
Medium_TOP 1	25 4	48	1.9 8	2	1.021	1.04 3	1.506	0.153	2.23 8	0.30 4	1	2	2
Medium_TOP 2	25 2	50	1.9 6	2	0.876	0.76 8	1.395	0.153	2.59 3	0.30 6	1	2	2
Medium_TOP 3	25 1	51	2 2	2	0.892	0.79 6	1.321	0.154	2.33 9	0.30 6	1	2	2
Medium_TOP 4	26 1	41	2.0 7	2	0.854	0.72 9	1.316	0.151	2.40 7	0.3	2	2	2
Medium_TOP 5	24 2	60	2.0 3	2	0.953	0.90 8	1.335	0.156	2.01	0.31 2	1	2	2
Medium_TOP 6	24 0	62	2.1 6	2	1.147	1.31 7	1.203	0.157	0.77 2	0.31 3	1	2	2
MOD_COD_ ELEC	30 2	0	1.6 7	2	0.473	0.22 3	- 0.705	0.14	- 1.51 3	0.28	1	2	2
MOD_COD_ GR	30 2	0	1.5 3	2	0.5	0.25	- 0.133	0.14	- 1.99 5	0.28	1	2	2

MOD_COD_F D	30 2	0	1.7 3	2	0.444	0.19 7	- 1.052	0.14	-0.9	0.28	1	2	2
MOD_COD_ TRVL	30 2	0	1.8 4	2	0.366	0.13 4	- 1.875	0.14	1.52 6	0.28	2	2	2
MOD_COD_F ashion	30 2	0	1.7 4	2	0.44	0.19 4	-1.09	0.14	0.81 7	0.28	1	2	2
MOD_COD_ Others	30 2	0	1.7	2	0.461	0.21 3	- 0.853	0.14	- 1.28 1	0.28	1	2	2
MOD_CC_EL EC	30 2	0	1.3 2	1	0.466	0.21 8	0.786	0.14	- 1.39 1	0.28	1	1	2
MOD_CC_G R	30 2	0	1.6 4	2	0.48	0.23	- 0.597	0.14	- 1.65 4	0.28	1	2	2
MOD_CC_FD	30 2	0	1.6 7	2	0.471	0.22 2	- 0.721	0.14	- 1.49	0.28	1	2	2
MOD_CC_TR VL	30 2	0	1.5 9	2	0.492	0.24 2	- 0.379	0.14	- 1.86 9	0.28	1	2	2
MOD_CC_FA SHION	30 2	0	1.6 2	2	0.486	0.23 7	- 0.493	0.14	- 1.76 8	0.28	1	2	2

MOD_CC_Others	30 2	0	1.7 3	2	0.444	0.19 7	- 1.052	0.14	-0.9	0.28	1	2	2
MOD_DCIB_ELEC	30 2	0	1.5 5	2	0.498	0.24 8	- 0.201	0.14	- 1.97 3	0.28	1	2	2
MOD_DCIB_GR	30 2	0	1.4 4	1	0.497	0.24 7	0.255	0.14	- 1.94 8	0.28	1	1	2
MOD_DCIB_FD	30 2	0	1.5 2	2	0.501	0.25 1	- 0.067	0.14	- 2.00 9	0.28	1	2	2
MOD_DCIB_TRVL	30 2	0	1.7 2	2	0.449	0.20 1	- 0.995	0.14	- 1.01 6	0.28	1	2	2
MOD_DCIB_FASHIOM	30 2	0	1.7 5	2	0.435	0.18 9	-1.15	0.14	- 0.68 1	0.28	1	2	2
MOD_DCIB_Others	30 2	0	1.7 1	2	0.455	0.20 7	- 0.923	0.14	- 1.15 6	0.28	1	2	2
MOD_UPI_ELEC	30 2	0	1.6 9	2	0.464	0.21 5	- 0.819	0.14	- 1.33 8	0.28	1	2	2

MOD_UPI_G R	30 2	0	1.5 5	2	0.498	0.24 8	- 0.214	0.14	- 1.96 7	0.28	1	2	2
MOD_UPI_F D	30 2	0	1.3 3	1	0.471	0.22 2	0.721	0.14	- 1.49	0.28	1	1	2
MOD_UPI_T RVL	30 2	0	1.7	2	0.461	0.21 3	- 0.853	0.14	- 1.28 1	0.28	1	2	2
MOD_UPI_F ASHION	30 2	0	1.6 7	2	0.473	0.22 3	- 0.705	0.14	- 1.51 3	0.28	1	2	2
MOD_UPI_Ot hers	30 2	0	1.7 4	2	0.442	0.19 5	- 1.071	0.14	- 0.85 9	0.28	1	2	2
MOD_DW_E LEC	30 2	0	1.7 5	2	0.433	0.18 7	- 1.171	0.14	- 0.63 4	0.28	1. 75	2	2
MOD_DW_G R	30 2	0	1.7 2	2	0.452	0.20 4	- 0.959	0.14	- 1.08 8	0.28	1	2	2
MOD_DW_F D	30 2	0	1.5 2	2	0.5	0.25	-0.08	0.14	- 2.00 7	0.28	1	2	2

MOD_DW_T RVL	30 2	0	1.7 8	2	0.416	0.17 3	- 1.346	0.14	- 0.19 1	0.28	2	2	2
MOD_DW_Fa shion	30 2	0	1.7 7	2	0.418	0.17 5	- 1.323	0.14	- 0.25 3	0.28	2	2	2
MOD_DW_Ot hers	30 2	0	1.6 9	2	0.462	0.21 4	- 0.836	0.14	- 1.30 9	0.28	1	2	2
MOD_BNPL_ ELEC	30 2	0	1.5 7	2	0.496	0.24 6	- 0.269	0.14	- 1.94 1	0.28	1	2	2
MOD_BNPL_ GR	30 2	0	1.8 5	2	0.353	0.12 5	- 2.019	0.14	2.08 8	0.28	2	2	2
MOD_BNPL_ FD	30 2	0	1.8 4	2	0.366	0.13 4	- 1.875	0.14	1.52 6	0.28	2	2	2
MOD_BNPL_ TRVL	30 2	0	1.8 9	2	0.312	0.09 8	- 2.517	0.14	4.36 6	0.28	2	2	2
MOD_BNPL_ Fashion	30 2	0	1.8 4	2	0.363	0.13 2	- 1.909	0.14	1.65 7	0.28	2	2	2
MOD_BNPL_ Others	30 2	0	1.6 2	2	0.486	0.23 6	- 0.508	0.14	- 1.75 4	0.28	1	2	2
VALUE_COD _LT100	30 2	0	1.7 9	2	0.405	0.16 4	- 1.467	0.14	0.15 2	0.28	2	2	2

VALUE_COD _100_1K	30 2	0	1.6 4	2	0.482	0.23 2	- 0.567	0.14	- 1.69	0.28	1	2	2
VALUE_COD _1K_20K	30 2	0	1.8 4	2	0.366	0.13 4	- 1.875	0.14	1.52 6	0.28	2	2	2
VALUE_COD _GT20K	30 2	0	1.9 5	2	0.211	0.04 4	- 4.337	0.14	16.9 19	0.28	2	2	2
VALUE_CC_ LT100	30 2	0	1.8 7	2	0.332	0.11	- 2.268	0.14	3.16 3	0.28	2	2	2
VALUE_CC_ 100_1K	30 2	0	1.7 8	2	0.412	0.16 9	- 1.393	0.14	- 0.06 1	0.28	2	2	2
VALUE_CC_ 1K_20K	30 2	0	1.7 2	2	0.45	0.20 3	- 0.977	0.14	- 1.05 3	0.28	1	2	2
VALUE_CC_ GT20K	30 2	0	1.7 2	2	0.452	0.20 4	- 0.959	0.14	- 1.08 8	0.28	1	2	2
VALUE_DCI B_LT100	30 2	0	1.8 7	2	0.34	0.11 5	- 2.179	0.14	2.76 8	0.28	2	2	2
VALUE_DCI B_100_1K	30 2	0	1.7 2	2	0.452	0.20 4	- 0.959	0.14	- 1.08 8	0.28	1	2	2
VALUE_DCI B_1K_20K	30 2	0	1.7 2	2	0.45	0.20 3	- 0.977	0.14	- 1.05 3	0.28	1	2	2

VALUE_DCI B_GT20K	30 2	0	1.6 7	2	0.471	0.22 2	- 0.721	0.14	- 1.49	0.28	1	2	2
VALUE_UPI_ LT100	30 2	0	1.8 3	2	0.372	0.13 9	- 1.809	0.14	1.27 9	0.28	2	2	2
VALUE_UPI_ 100_1K	30 2	0	1.6 5	2	0.479	0.23	- 0.612	0.14	- 1.63 6	0.28	1	2	2
VALUE_UPI_ 1K_20K	30 2	0	1.7	2	0.46	0.21 1	-0.87	0.14	1.25 1	0.28	1	2	2
VALUE_UPI_ GT20K	30 2	0	1.6 7	2	0.473	0.22 3	- 0.705	0.14	- 1.51 3	0.28	1	2	2
VALUE_DW _LT100	30 2	0	1.7 2	2	0.452	0.20 4	- 0.959	0.14	- 1.08 8	0.28	1	2	2
VALUE_DW _100_1K	30 2	0	1.6 7	2	0.471	0.22 2	- 0.721	0.14	- 1.49	0.28	1	2	2
VALUE_DW _1K_20K	30 2	0	1.8 6	2	0.35	0.12 3	- 2.057	0.14	2.24 6	0.28	2	2	2
VALUE_DW _GT20K	30 2	0	1.9 3	2	0.249	0.06 2	- 3.506	0.14	10.3 61	0.28	2	2	2
VALUE_BNP L_LT100	30 2	0	1.6 5	2	0.477	0.22 8	- 0.643	0.14	- 1.59 7	0.28	1	2	2

VALUE_BNP L_100_1K	30 2	0	1.7 7	2	0.418	0.17 5	- 1.323	0.14	- 0.25 3	0.28	2	2	2
VALUE_BNP L_1K_20K	30 2	0	1.8 8	2	0.328	0.10 8	- 2.314	0.14	3.37 7	0.28	2	2	2
VALUE_BNP L_GT20K	30 2	0	1.9 3	2	0.26	0.06 8	- 3.304	0.14	8.97 4	0.28	2	2	2

Table 57: Final Data Descriptive Analysis

Factors	Mean	Median	Observed maximum	Standard deviation	Excess kurtosis	Skewness	Number of observations used	Cramér-von Mises test statistic	Cramér-von Mises p value	
1clickPayment	2.275	2.000	1.000	7.000	1.225	1.384	98	201.000	1.365	0.000
Age	24.78	27.000	1.000	5.000	0.655	0.503	98	201.000	3.722	0.000
BI2	2.1	2.000	1.000	7.000	1.231	2.039	41	201.000	2.006	0.000

	8									
	9									
	2.									
	5	2.								
	9	00	1.0				0.8			
BI3	7	0	00	7.000	1.368	0.536	75	201.000	1.249	0.000
	1.									
	9	1.								
	7	00	1.0				1.4			
BI5	5	0	00	7.000	1.317	1.718	40	201.000	3.363	0.000
	2.									
	3	2.								
	4	00	1.0				1.1			
BI6	3	0	00	7.000	1.573	0.416	11	201.000	2.264	0.000
	1.									
	9	1.								
	1	91	1.0				1.6			
Discount	7	7	00	7.000	1.074	3.389	30	201.000	2.531	0.000
	1.									
	6	1.								
	9	00	1.0				2.4			
EE2	2	0	00	7.000	1.090	7.522	02	201.000	4.237	0.000
	2.									
	2.	00	1.0				1.5			
EE3	1	0	00	7.000	1.329	2.505	09	201.000	2.252	0.000

	7 4									
Ease_pay ment	1. 9 8 9	2. 00 0	1.0 00	6.000	1.088	2.075	1.4 71	201.000	3.062	0.000
FC1	2. 0 5 5	2. 00 0	1.0 00	7.000	1.274	2.705	1.5 97	201.000	2.566	0.000
FC4	1. 9 8 0	2. 00 0	1.0 00	7.000	1.238	2.947	1.6 56	201.000	2.906	0.000
Freq_TO P1	1. 8 4 6	2. 00 0	1.0 00	3.000	0.680	- 0.800	0.2 65	201.000	2.354	0.000
Freq_TO P2	2. 1 7	2. 00 0	1.0 00	3.000	0.768	- 1.271	- 0.2 30	201.000	2.062	0.000
Freq_TO P3	2. 0	2. 00 0	1.0 00	3.000	0.706	- 0.985	- 0.1 10	201.000	2.535	0.000

	6 2									
Freq_TO P4	2. 4 7 5	3. 00 0	1.0 1.0	3.000	0.633	- 0.004	- 0.9 67	201.000	3.100	0.000
Freq_TO P5	1. 8 0 0	2. 00 0	1.0 1.0	3.000	0.708	- 0.931	0.3 66	201.000	2.141	0.000
Freq_TO P6	1. 4 5 5	1. 00 0	1.0 1.0	3.000	0.639	0.529	1.2 68	201.000	4.161	0.000
Gender	1. 2 7 9	1. 00 0	1.0 1.0	2.000	0.448	- 1.020	0.9 95	201.000	8.329	0.000
Geopoliti cal	2. 5 4 5	2. 54 5	1.0 1.0	7.000	1.189	0.080	0.5 18	201.000	0.765	0.000
Govern_ Policy	2. 2 3	2. 00 0	1.0 1.0	7.000	1.214	0.823	0.8 46	201.000	1.006	0.000

	8									
	8									
	2.									
	2	2.								
	1	00	1.0				1.3			
HM1	4	0	00	7.000	1.319	1.983	81	201.000	1.994	0.000
	2.									
	1	2.								
	0	00	1.0				1.4			
HM2	9	0	00	7.000	1.249	2.582	58	201.000	2.076	0.000
	1.									
	7	1.								
High_sec	9	79	1.0				1.6			
urity	2	2	00	6.000	1.054	2.545	26	201.000	3.123	0.000
	2.									
	2	2.								
	1	00	1.0			-	0.5			
Income	9	0	00	5.000	1.173	0.907	17	201.000	1.714	0.000
	0.									
	1	0.								
MOD_B	9	00	0.0				1.5			
NPL_FD	4	0	00	1.000	0.395	0.435	59	201.000	10.464	0.000
	0.									
MOD_B	0.	00	0.0				1.7			
NPL_GR	1	0	00	1.000	0.379	1.008	32	201.000	11.048	0.000

	7									
	4									
MOD_B	0.									
NPL_TR	1	0.								
VL	1	00	0.0				2.3			
	9	0	00	1.000	0.324	3.630	65	201.000	12.790	0.000
MOD_C	0.									
C_FASH	4	0.								
ION	6	00	0.0			-	0.1			
	3	0	00	1.000	0.499	1.997	51	201.000	5.936	0.000
MOD_C	0.									
C_GR	4	0.								
	1	00	0.0			-	0.3			
	3	0	00	1.000	0.492	1.892	56	201.000	6.253	0.000
MOD_C	0.									
C_TRVL	5	1.								
	0	00	0.0			-	0.0			
	2	0	00	1.000	0.500	2.020	10	201.000	5.865	0.000
MOD_D	0.									
W_FD	3	0.								
	2	00	0.0			-	0.7			
	3	0	00	1.000	0.468	1.436	61	201.000	7.447	0.000
MOD_U	0.									
PI_FAS	0.	00	0.0			-	0.4			
HION	3	0	00	1.000	0.488	1.823	41	201.000	6.451	0.000

	9 3									
MOD_U PI_FD	0. 5 8 2	1. 00 0	0.0 00	1.000	0.493	1.907	- 0.3 35	201.000	6.210	0.000
MOD_U PI_GR	0. 5 3 2	1. 00 0	0.0 00	1.000	0.499	2.003	- 0.1 31	201.000	5.918	0.000
Merc_Ac ce	2. 0 5 0	2. 00 0	1.0 00	5.000	1.033	0.141	0.9 03	201.000	2.133	0.000
PE1	2. 1 9 9	2. 00 0	1.0 00	7.000	1.281	1.508	1.2 95	201.000	2.007	0.000
PE3	2. 1 9	2. 00 0	1.0 00	7.000	1.161	1.746	1.2 43	201.000	2.012	0.000
PP1	2. 2 3	2. 00 0	1.0 00	7.000	1.411	1.116	1.2 22	201.000	1.967	0.000

	2									
	3									
	2.									
	8	2.								
	2	00	1.0			-	0.7			
PP2	1	0	00	7.000	1.666	0.216	75	201.000	1.222	0.000
	2.									
	2	2.								
	5	00	1.0				1.2			
PP3	4	0	00	7.000	1.379	1.520	68	201.000	1.931	0.000
	2.									
	2	2.								
	0	00	1.0				1.4			
PP4	4	0	00	7.000	1.354	1.901	53	201.000	2.662	0.000
	2.									
	4	2.								
Promo_	1	00	1.0				0.7			
Advert	0	0	00	7.000	1.131	0.817	78	201.000	0.963	0.000
	2.									
	2	2.								
	5	00	1.0				1.2			
Reviews	0	0	00	7.000	1.252	1.865	65	201.000	1.544	0.000
	1.									
	1.	97	1.0				1.8			
Rewards	9	2	00	7.000	1.314	3.727	44	201.000	3.283	0.000

	7									
	2									
SI1	2.428	2.000	1.000	6.000	1.299	-0.016	0.798	201.000	1.428	0.000
Si2	2.214	2.000	1.000	6.000	1.209	0.063	0.875	201.000	1.799	0.000
T1	2.592	2.000	1.000	7.000	1.572	0.751	1.084	201.000	1.405	0.000
T2	2.219	2.000	1.000	7.000	1.473	1.192	1.318	201.000	2.568	0.000
UI_CX	2.161	2.000	1.000	5.000	1.064	-0.564	0.655	201.000	1.751	0.000
VALUE _CC_GT 20K	0.03	0.000	0.000	1.000	0.482	-1.714	0.551	201.000	6.752	0.000

	6									
	8									
VALUE	0.									
DCIB	2 0.									
GT20K	1 00	0.0				-	1.4			
	4 0	00	1.000	0.410	0.024	06	201.000	9.910	0.000	
VALUE	0.									
_DW_G	0 0.									
T20K	7 00	0.0					3.2			
	5 0	00	1.000	0.263	8.726	62	201.000	14.332	0.000	
VALUE	0.									
_UPI_G	1 0.									
T20K	9 00	0.0					1.5			
	9 0	00	1.000	0.399	0.311	19	201.000	10.323	0.000	
	2.									
	6 2.									
WOM	2 62	1.0					0.6			
	4 4	00	7.000	1.147	0.627	05	201.000	0.807	0.000	
Widespre	2.									
ad_availa	1 2.									
bility	6 00	1.0					1.0			
	3 0	00	7.000	1.129	1.352	62	201.000	1.548	0.000	

Appendix 4: Documents

1. Output file detailing the K_Mean_Clustering & Hierarchical Clustering and relevant clusters

Appendix 5: Output14 file detailing Hierarchical Clustering**Proximity matrix**

Table 58: Proximity Matrix

Case	MO D_C	MO OD_ ELE C	MO D_C D_C OD_ OD_ TRV L	MO D_C D_C OD_ OD_ Fashi on	MO D_C D_C OD_ OD_ Othe rs	MO D_C D_C OD_ OD_ C_E LEC	MO D_C D_C OD_ OD_ C_G R	MO D_C D_C OD_ OD_ C_F D	MO D_C D_C OD_ OD_ C_T RVL	MO D_C D_C OD_ OD_ ASH ION	MO D_C D_C OD_ OD_ C_Ot hers	
MO D_C OD_ ELE C	0.00	9.64	9.05	8.42	8.944	10.9	11.1	10.2	10.2	10.58	10.39	9.95
MO D_C OD_ GR	9.64	0.00	7.93	7.74	8.426	10.3	9.64	9.79	9.48	10.34	9.747	9.48
MO D_C OD_ FD	9.05	7.93	0.00	6.70	8.124	10.1	9.89	9.43	9.64	9.798	9.274	9.43
MO D_C OD_ FD	8.42	7.74	6.70	0.00	7.141	9.32	11.1	9.05	8.60	9.950	9.539	8.60

TRV L												
MO D_C OD_ Fashi on	8.94 4	8.42 6	8.12 4	7.14 1	0.000	9.59 2	10.5 83	9.32 7	8.88 8	9.592	9.695	8.66 0
MO D_C OD_ Other s	10.9 54	10.3 44	10.1 00	9.32 7	9.592	0.00 0	10.1 98	9.53 9	9.74 7	9.695	9.592	8.66 0
MO D_C C_E LEC	11.1 36	9.64 4	9.89 9	11.1 80	10.58 3	10.1 98	0.00 0	9.32 7	9.32 7	9.055	8.367	10.9 09
MO D_C C_G R	10.2 47	9.79 8	9.43 4	9.05 5	9.327	9.53 9	9.32 7	0.00 0	6.48 1	7.810	7.416	9.27 4
MO D_C C_F D	10.2 47	9.48 7	9.64 4	8.60 2	8.888	9.74 7	9.32 7	6.48 1	0.00 0	7.681	7.280	8.71 8

MO	10.5	10.3	9.79	9.95	9.592	9.69	9.05	7.81	7.68	0.000	6.928	9.22
D_C	83	44	8	0		5	5	0	1			0
C_T												
RVL												
MO	10.3	9.74	9.27	9.53	9.695	9.59	8.36	7.41	7.28	6.928	0.000	9.11
D_C	92	7	4	9		2	7	6	0			0
C_F												
ASH												
ION												
MO	9.95	9.48	9.43	8.60	8.660	8.66	10.9	9.27	8.71	9.220	9.110	0.00
D_C	0	7	4	2		0	09	4	8			0
C_Ot												
hers												
MO	9.48	7.93	8.71	7.55	9.165	9.89	9.48	9.43	9.00	10.10	9.487	9.53
D_D	7	7	8	0		9	7	4	0	0		9
CIB_												
ELE												
C												
MO	10.1	8.77	10.1	9.64	9.695	10.3	10.1	9.64	9.74	9.899	10.00	10.6
D_D	98	5	00	4		92	00	4	7		0	30
CIB_												
GR												
MO	9.89	8.42	9.38	8.06	8.485	9.89	9.69	9.11	8.66	9.592	9.165	9.43
D_D	9	6	1	2		9	5	0	0			4

CIB_ FD												
MO D_D CIB_ TRV L	9.11 0	8.83 2	8.42 6	8.12 4	8.185	9.53 9	10.6 30	9.48 7	9.27 4	9.950	9.539	9.38 1
MO D_D CIB_ FAS HIO M	9.00 0	8.94 4	8.30 7	7.48 3	8.775	9.84 9	10.8 17	9.16 5	8.83 2	9.644	8.544	8.71 8
MO D_D CIB_ Other s	10.0 00	9.74 7	9.27 4	9.11 0	10.00 0	8.24 6	10.2 96	9.43 4	9.32 7	9.592	9.055	8.06 2
MO D_U PI_E LEC	9.22 0	8.71 8	8.54 4	8.00 0	8.660	9.64 4	9.84 9	9.05 5	9.16 5	9.434	9.434	9.69 5
MO D_U	9.89 9	9.95 0	10.1 00	10.0 50	9.695	10.2 96	10.3 92	9.43 4	9.00 0	9.274	8.832	9.95 0

PI_G R												
MO D_U PI_F D	10.3 92	10.0 50	10.8 63	11.0 00	10.29 6	10.5 83	8.83 2	9.53 9	9.64 4	9.055	8.832	10.0 50
MO D_U PI_T RVL	9.64 4	8.71 8	8.54 4	8.00 0	8.775	9.53 9	10.0 50	8.71 8	8.94 4	9.539	9.110	9.27 4
MO D_U PI_F ASH ION	9.89 9	9.11 0	8.94 4	8.66 0	9.274	9.79 8	10.1 00	8.88 8	9.22 0	8.944	8.718	9.43 4
MO D_U PI_O thers	10.0 00	9.32 7	8.24 6	8.30 7	9.165	8.48 5	9.89 9	8.54 4	9.11 0	9.274	8.832	8.54 4
MO D_D W_E LEC	8.36 7	8.42 6	8.48 5	7.41 6	8.602	9.38 1	9.89 9	9.43 4	9.00 0	10.10 0	9.695	9.22 0
MO D_D	9.11 0	9.16 5	8.77 5	8.36 7	9.327	9.84 9	10.7 24	9.27 4	9.48 7	9.644	9.220	9.48 7

W_G R												
MO D_D W_F D	9.95 0	8.36 7	9.53 9	8.48 5	9.110	9.84 9	9.84 9	9.69 5	9.38 1	9.220	9.327	9.48 7
MO D_D W_T RVL	8.60 2	8.54 4	8.71 8	7.00 0	8.718	9.48 7	11.0 45	8.66 0	8.77 5	9.592	9.381	9.00 0
MO D_D W_F ashio n	9.22 0	8.24 6	8.06 2	6.92 8	8.660	9.43 4	10.7 24	9.16 5	8.83 2	9.327	9.110	8.71 8
MO D_D W_O thers	10.2 47	9.79 8	9.64 4	9.38 1	9.434	8.88 8	10.6 30	9.27 4	9.48 7	9.644	9.220	8.24 6
MO D_B NPL _EL EC	9.38 1	8.66 0	9.48 7	8.77 5	9.592	10.2 96	9.89 9	10.1 49	10.3 44	10.39 2	10.19 8	9.95 0

MO	9.05	8.18	8.48	7.14	8.367	9.59	11.4	8.54	8.88	10.10	10.10	8.77
D_B	5	5	5	1		2	02	4	8	0	0	5
NPL												
_GR												
MO	9.27	8.77	8.48	6.70	8.367	9.48	10.9	9.00	8.18	9.592	9.798	8.54
D_B	4	5	5	8		7	54	0	5			4
NPL												
_FD												
MO	9.11	9.05	8.54	6.00	7.937	9.22	11.3	9.16	8.94	9.849	9.747	8.71
D_B	0	5	4	0		0	58	5	4			8
NPL												
_TR												
VL												
MO	9.00	8.71	8.30	7.21	8.185	9.64	11.1	9.27	8.71	10.14	9.327	8.36
D_B	0	8	7	1		4	80	4	8	9		7
NPL												
_Fas												
hion												
MO	10.7	10.4	10.0	10.5	10.19	8.60	10.1	9.74	10.1	9.592	9.381	9.84
D_B	70	40	00	36	8	2	98	7	49			9
NPL												
_Oth												
ers												
VAL	10.5	9.79	9.95	9.16	10.24	9.32	11.1	9.79	10.2	10.53	10.34	9.48
UE_	36	8	0	5	7	7	80	8	96	6	4	7

COD _LT1 00												
VAL UE_ COD _100 _1K	10.2 47	9.69 5	9.22 0	9.79 8	9.747	10.6 30	10.1 49	10.0 00	10.3 92	10.05 0	10.05 0	9.69 5
VAL UE_ COD _1K_ 20K	9.38 1	9.43 4	9.38 1	8.06 2	8.367	9.48 7	11.8 32	10.9 09	10.3 44	10.77 0	10.77 0	9.22 0
VAL UE_ COD _GT 20K	9.16 5	8.88 8	8.36 7	6.24 5	8.246	9.05 5	11.7 47	9.84 9	9.22 0	10.48 8	10.00 0	8.77 5
VAL UE_ CC_ LT10 0	9.74 7	8.94 4	8.77 5	7.61 6	8.544	9.22 0	12.0 42	10.1 98	10.0 00	10.81 7	10.72 4	8.48 5
VAL UE_ 0	9.69 5	9.53 9	9.79 8	8.66 0	9.274	9.89 9	10.8 63	9.53 9	9.32 7	10.10 0	9.798	9.22 0

CC_ 100_ 1K												
VAL	10.6	10.2	10.0	9.89	9.849	9.84	10.3	9.16	9.48	9.327	9.110	9.38
UE_ CC_ 1K_2 0K	30	96	50	9		9	44	5	7			1
VAL	10.6	10.0	10.0	9.53	10.10	9.89	9.59	9.74	9.53	8.944	8.944	9.22
UE_ CC_ GT2 0K	77	50	00	9	0	9	2	7	9			0
VAL	9.84	9.27	8.66	7.87	9.110	9.32	11.0	9.79	9.69	10.44	10.34	8.71
UE_ DCI B_L T100	9	4	0	4		7	91	8	5	0	4	8
VAL	9.95	9.79	9.74	9.27	9.539	9.84	10.9	10.0	9.59	9.849	9.849	8.83
UE_ DCI B_10 0_1K	0	8	7	4		9	09	00	2			2
VAL	10.6	10.1	9.74	9.48	10.63	10.4	11.3	10.4	10.8	10.63	10.34	10.4
UE_	30	00	7	7	0	40	58	88	63	0	4	88

DCI B_1 K_20 K												
VAL UE_ DCI B_G T20 K	9.32 7	9.27 4	9.22 0	8.00 0	9.110	9.53 9	11.0 00	10.3 92	9.79 8	10.24 7	9.644	9.16 5
VAL UE_ UPI_ LT10 0	10.1 49	9.27 4	8.77 5	8.24 6	9.000	9.32 7	11.0 91	9.48 7	9.16 5	9.644	9.747	8.71 8
VAL UE_ UPI_ 100_ 1K	10.1 00	9.74 7	10.2 96	10.0 50	10.00 0	10.1 00	10.5 83	10.3 44	9.95 0	9.695	10.00 0	9.74 7
VAL UE_ UPI_ 1K_2 0K	10.0 50	10.1 00	10.2 47	9.89 9	9.849	10.3 44	11.0 00	10.0 00	10.1 00	10.63 0	10.34 4	9.48 7

	CIB _EL EC	CIB_ GR	CIB_ FD	CIB _TR VL	CIB_ FAS HIO M	CIB _Oth ers	PI_E LEC	PI_ GR	PI_F D	PI_T RVL	PI_F ASH ION	PI_O thers
MO D_C OD_ ELE C	9.48 7	10.1 98	9.89 9	9.11 0	9.000	10.0 00	9.22 0	9.89 9	10.3 92	9.644	9.899	10.0 00
MO D_C OD_ GR	7.93 7	8.77 5	8.42 6	8.83 2	8.944	9.74 7	8.71 8	9.95 0	10.0 50	8.718	9.110	9.32 7
MO D_C OD_ FD	8.71 8	10.1 00	9.38 1	8.42 6	8.307	9.27 4	8.54 4	10.1 00	10.8 63	8.544	8.944	8.24 6
MO D_C OD_ TRV L	7.55 0	9.64 4	8.06 2	8.12 4	7.483	9.11 0	8.00 0	10.0 50	11.0 00	8.000	8.660	8.30 7
MO D_C OD_ L	9.16 5	9.69 5	8.48 5	8.18 5	8.775	10.0 00	8.66 0	9.69 5	10.2 96	8.775	9.274	9.16 5

Fashi on												
MO D_C OD_ Other s	9.89 9	10.3 92	9.89 9	9.53 9	9.849	8.24 6	9.64 4	10.2 96	10.5 83	9.539	9.798	8.48 5
MO D_C C_E LEC	9.48 7	10.1 00	9.69 5	10.6 30	10.81 7	10.2 96	9.84 9	10.3 92	8.83 2	10.05 0	10.10 0	9.89 9
MO D_C C_G R	9.43 4	9.64 4	9.11 0	9.48 7	9.165	9.43 4	9.05 5	9.43 4	9.53 9	8.718	8.888	8.54 4
MO D_C C_F D	9.00 0	9.74 7	8.66 0	9.27 4	8.832	9.32 7	9.16 5	9.00 0	9.64 4	8.944	9.220	9.11 0
MO D_C C_T RVL	10.1 00	9.89 9	9.59 2	9.95 0	9.644	9.59 2	9.43 4	9.27 4	9.05 5	9.539	8.944	9.27 4
MO D_C	9.48 7	10.0 00	9.16 5	9.53 9	8.544	9.05 5	9.43 4	8.83 2	8.83 2	9.110	8.718	8.83 2

C_F ASH ION												
MO D_C C_Ot hers	9.53 9	10.6 30	9.43 4	9.38 1	8.718	8.06 2	9.69 5	9.95 0	10.0 50	9.274	9.434	8.54 4
MO D_D CIB_ ELE C	0.00 0	8.94 4	7.61 6	8.42 6	7.810	10.0 00	7.68 1	9.89 9	9.89 9	8.307	8.602	8.94 4
MO D_D CIB_ GR	8.94 4	0.00 0	7.74 6	8.77 5	8.775	11.3 14	9.32 7	9.27 4	9.27 4	8.426	8.944	10.1 00
MO D_D CIB_ FD	7.61 6	7.74 6	0.00 0	7.93 7	7.937	10.2 96	8.66 0	9.27 4	9.16 5	7.810	8.367	9.27 4
MO D_D CIB_ TRV L	8.42 6	8.77 5	7.93 7	0.00 0	7.483	9.74 7	8.83 2	9.00 0	9.43 4	8.000	8.888	9.00 0

MO	7.81	8.77	7.93	7.48	0.000	8.54	8.48	9.22	10.4	7.348	7.810	8.18
D_D	0	5	7	3		4	5	0	40			5
CIB_												
FAS												
HIO												
M												
MO	10.0	11.3	10.2	9.74	8.544	0.00	9.95	10.0	10.5	9.434	9.274	7.21
D_D	00	14	96	7		0	0	00	83			1
CIB_												
Other												
s												
MO	7.68	9.32	8.66	8.83	8.485	9.95	0.00	8.88	10.0	5.657	7.000	8.66
D_U	1	7	0	2		0	0	8	50			0
PI_E												
LEC												
MO	9.89	9.27	9.27	9.00	9.220	10.0	8.88	0.00	8.48	7.937	8.485	10.1
D_U	9	4	4	0		00	8	0	5			98
PI_G												
R												
MO	9.89	9.27	9.16	9.43	10.44	10.5	10.0	8.48	0.00	9.539	9.274	10.9
D_U	9	4	5	4	0	83	50	5	0			54
PI_F												
D												
MO	8.30	8.42	7.81	8.00	7.348	9.43	5.65	7.93	9.53	0.000	6.083	8.18
D_U	7	6	0	0		4	7	7	9			5

PI_T RVL												
MO D_U PI_F ASH ION	8.60 2	8.94 4	8.36 7	8.88 8	7.810	9.27 4	7.00 0	8.48 5	9.27 4	6.083	0.000	8.48 5
MO D_U PI_O thers	8.94 4	10.1 00	9.27 4	9.00 0	8.185	7.21 1	8.66 0	10.1 98	10.9 54	8.185	8.485	0.00 0
MO D_D W_E LEC	7.48 3	9.38 1	8.60 2	7.81 0	7.810	9.79 8	7.68 1	9.79 8	10.3 92	8.307	8.944	9.05 5
MO D_D W_G R	8.66 0	9.00 0	8.66 0	8.12 4	7.746	9.53 9	8.60 2	9.11 0	10.0 50	8.000	8.660	8.66 0
MO D_D W_F D	8.18 5	8.66 0	7.55 0	8.24 6	8.485	10.0 50	8.83 2	9.22 0	8.66 0	8.367	8.775	9.22 0
MO D_D	7.87 4	8.60 2	8.48 5	7.93 7	7.141	9.27 4	8.30 7	9.48 7	10.4 88	7.937	8.485	8.48 5

W_T RVL												
MO D_D W_F ashio n	7.93 7	8.77 5	7.93 7	7.61 6	6.325	8.88 8	8.00 0	9.74 7	10.6 30	7.348	7.416	7.93 7
MO D_D W_O thers	10.2 47	10.6 30	9.84 9	9.48 7	9.055	6.70 8	9.69 5	9.43 4	10.6 30	9.055	9.327	7.93 7
MO D_B NPL _EL EC	8.00 0	9.59 2	9.89 9	9.64 4	9.327	10.2 96	9.00 0	10.8 63	10.1 00	9.434	10.19 8	9.89 9
MO D_B NPL _GR	8.36 7	9.05 5	8.48 5	7.68 1	7.550	9.16 5	7.93 7	9.69 5	11.0 45	7.550	8.718	8.60 2
MO D_B NPL _FD	8.48 5	9.59 2	8.24 6	8.54 4	7.937	9.59 2	8.18 5	9.89 9	10.7 70	7.937	8.718	8.60 2

VAL	9.48	10.3	9.16	9.22	9.327	8.94	9.64	10.4	10.8	9.644	9.899	9.38
UE_ COD _1K_ 20K	7	92	5	0		4	4	88	63			1
VAL	8.24	10.2	9.05	8.77	8.185	9.16	8.88	10.7	11.5	8.775	9.381	8.60
UE_ COD _GT 20K	6	96	5	5		5	8	70	76			2
VAL	9.43	10.5	9.43	9.16	8.718	9.11	9.38	10.6	11.7	9.381	9.539	9.11
UE_ CC_ LT10 0	4	36	4	5		0	1	30	05			0
VAL	9.48	10.3	9.59	10.0	9.434	9.05	9.32	11.1	11.0	9.747	10.10	8.94
UE_ CC_ 100_ 1K	7	92	2	50		5	7	36	45		0	4
VAL	10.4	10.7	10.6	9.69	10.19	9.74	10.0	9.95	9.84	9.592	9.747	9.64
UE_ CC_ 1K_2 0K	40	24	30	5	8	7	00	0	9			4

T20 K												
VAL	9.43	10.8	10.0	9.38	9.274	8.77	9.38	11.0	11.0	9.695	9.539	8.77
UE_ UPI_ LT10 0	4	17	50	1		5	1	00	00			5
VAL	10.3	10.3	10.4	10.1	10.14	10.0	10.1	9.89	10.1	10.44	10.58	10.1
UE_ UPI_ 100_ 1K	92	92	88	49	9	00	49	9	00	0	3	98
VAL	10.2	10.3	9.64	9.89	9.695	10.1	9.69	9.43	10.1	9.055	9.644	10.4
UE_ UPI_ 1K_2 0K	47	44	4	9		49	5	4	49			40
VAL	8.36	9.89	8.60	8.88	8.426	9.38	8.30	10.0	10.2	8.307	8.832	8.83
UE_ UPI_ GT2 0K	7	9	2	8		1	7	00	96			2
VAL	10.6	10.6	10.4	10.1	10.29	9.64	10.1	9.95	10.9	10.29	10.24	9.74
UE_ DW_	30	30	40	98	6	4	00	0	09	6	7	7

LT10 0												
VAL	10.0	10.8	10.3	9.79	10.00	9.95	10.0	11.0	9.95	10.39	10.44	9.64
UE_ DW_ 100_ 1K	50	17	44	8	0	0	00	00	0	2	0	4
VAL	8.88	9.43	9.00	9.05	8.718	9.43	9.69	10.3	10.9	9.055	9.539	9.43
UE_ DW_ 1K_2 0K	8	4	0	5		4	5	44	09			4
VAL	8.12	10.3	8.83	8.66	8.062	9.05	8.77	10.5	11.3	8.660	9.487	8.60
UE_ DW_ GT2 0K	4	92	2	0		5	5	83	14			2
VAL	10.5	10.9	10.4	10.5	10.53	10.1	10.4	10.3	9.59	10.53	10.29	10.3
UE_ BNP L_L T100	83	54	88	36	6	00	40	92	2	6	6	92
VAL	9.53	10.2	9.74	9.27	9.055	9.22	9.38	10.7	11.1	9.487	9.950	8.88
UE_ BNP	9	47	7	4		0	1	24	80			8

ELE C												
MO D_C OD_ GR	8.42 6	9.16 5	8.36 7	8.54 4	8.246	9.79 8	8.66 0	8.18 5	8.77 5	9.055	8.718	10.4 40
MO D_C OD_ FD	8.48 5	8.77 5	9.53 9	8.71 8	8.062	9.64 4	9.48 7	8.48 5	8.48 5	8.544	8.307	10.0 00
MO D_C OD_ TRV L	7.41 6	8.36 7	8.48 5	7.00 0	6.928	9.38 1	8.77 5	7.14 1	6.70 8	6.000	7.211	10.5 36
MO D_C OD_ Fashi on	8.60 2	9.32 7	9.11 0	8.71 8	8.660	9.43 4	9.59 2	8.36 7	8.36 7	7.937	8.185	10.1 98
MO D_C OD_ Other s	9.38 1	9.84 9	9.84 9	9.48 7	9.434	8.88 8	10.2 96	9.59 2	9.48 7	9.220	9.644	8.60 2

ASH ION												
MO D_U PI_O thers	9.05 5	8.66 0	9.22 0	8.48 5	7.937	7.93 7	9.89 9	8.60 2	8.60 2	8.544	8.062	8.71 8
MO D_D W_E LEC	0.00 0	8.30 7	8.66 0	7.21 1	7.141	10.3 44	7.74 6	7.34 8	7.07 1	7.416	7.550	10.7 70
MO D_D W_G R	8.30 7	0.00 0	8.00 0	7.68 1	7.483	10.2 96	9.11 0	7.41 6	7.81 0	8.000	8.000	10.8 17
MO D_D W_F D	8.66 0	8.00 0	0.00 0	7.93 7	7.746	10.5 83	9.00 0	8.42 6	8.66 0	8.602	8.718	10.5 36
MO D_D W_T RVL	7.21 1	7.68 1	7.93 7	0.00 0	6.245	9.64 4	8.60 2	6.92 8	7.48 3	6.856	7.000	10.2 96
MO D_D W_F	7.14 1	7.48 3	7.74 6	6.24 5	0.000	9.48 7	8.88 8	7.28 0	7.28 0	7.211	6.782	9.84 9

ashio n												
MO D_D W_O thers	10.3 44	10.2 96	10.5 83	9.64 4	9.487	0.00 0	10.5 36	9.22 0	9.84 9	9.592	9.592	7.93 7
MO D_B NPL _EL EC	7.74 6	9.11 0	9.00 0	8.60 2	8.888	10.5 36	0.00 0	8.36 7	8.48 5	8.426	8.888	12.0 00
MO D_B NPL _GR	7.34 8	7.41 6	8.42 6	6.92 8	7.280	9.22 0	8.36 7	0.00 0	5.65 7	5.916	6.856	10.8 63
MO D_B NPL _FD	7.07 1	7.81 0	8.66 0	7.48 3	7.280	9.84 9	8.48 5	5.65 7	0.00 0	5.916	7.000	10.8 63
MO D_B NPL _TR VL	7.41 6	8.00 0	8.60 2	6.85 6	7.211	9.59 2	8.42 6	5.91 6	5.91 6	0.000	6.325	10.5 36

LT10 0												
VAL	10.0	9.74	10.0	9.79	10.05	9.84	9.69	9.79	9.79	9.539	9.950	10.2
UE_ UPI_ 100_ 1K	00	7	50	8	0	9	5	8	8			96
VAL	9.95	9.69	9.89	10.1	9.899	10.1	10.2	9.53	9.43	9.381	9.695	9.74
UE_ UPI_ 1K_2 0K	0	5	9	49		00	47	9	4			7
VAL	8.60	8.77	8.18	8.12	8.185	9.95	8.94	8.00	7.87	7.810	7.810	10.4
UE_ UPI_ GT2 0K	2	5	5	4		0	4	0	4			88
VAL	10.7	10.3	10.8	10.4	10.58	8.94	10.5	10.0	10.4	9.695	10.29	9.43
UE_ DW_ LT10 0	24	92	63	40	3	4	36	50	40		6	4
VAL	9.84	9.89	9.48	9.95	10.00	10.1	9.84	9.53	9.74	9.695	9.592	10.0
UE_ DW_	9	9	7	0	0	98	9	9	7			50

MO	9.95	9.22	9.38	8.36	8.775	9.79	10.0	10.0	8.66	9.747	9.747	9.22
D_C	0	0	1	7		8	50	00	0			0
OD_												
FD												
MO	9.16	9.79	8.06	6.24	7.616	8.66	9.89	9.53	7.87	9.274	9.487	8.00
D_C	5	8	2	5		0	9	9	4			0
OD_												
TRV												
L												
MO	10.2	9.74	8.36	8.24	8.544	9.27	9.84	10.1	9.11	9.539	10.63	9.11
D_C	47	7	7	6		4	9	00	0		0	0
OD_												
Fashi												
on												
MO	9.32	10.6	9.48	9.05	9.220	9.89	9.84	9.89	9.32	9.849	10.44	9.53
D_C	7	30	7	5		9	9	9	7		0	9
OD_												
Other												
s												
MO	11.1	10.1	11.8	11.7	12.04	10.8	10.3	9.59	11.0	10.90	11.35	11.0
D_C	80	49	32	47	2	63	44	2	91	9	8	00
C_E												
LEC												
MO	9.79	10.0	10.9	9.84	10.19	9.53	9.16	9.74	9.79	10.00	10.48	10.3
D_C	8	00	09	9	8	9	5	7	8	0	8	92

C_G R												
MO D_C C_F D	10.2 96	10.3 92	10.3 44	9.22 0	10.00 0	9.32 7	9.48 7	9.53 9	9.69 5	9.592	10.86 3	9.79 8
MO D_C C_T RVL	10.5 36	10.0 50	10.7 70	10.4 88	10.81 7	10.1 00	9.32 7	8.94 4	10.4 40	9.849	10.63 0	10.2 47
MO D_C C_F ASH ION	10.3 44	10.0 50	10.7 70	10.0 00	10.72 4	9.79 8	9.11 0	8.94 4	10.3 44	9.849	10.34 4	9.64 4
MO D_C C_Ot hers	9.48 7	9.69 5	9.22 0	8.77 5	8.485	9.22 0	9.38 1	9.22 0	8.71 8	8.832	10.48 8	9.16 5
MO D_D CIB_ ELE C	10.0 50	10.1 49	9.48 7	8.24 6	9.434	9.48 7	10.4 40	9.59 2	9.53 9	10.05 0	9.644	8.54 4

MO D_U PI_E LEC	9.38 1 96 4 8	10.2 96 4 8	9.64 4 8	8.88 8	9.381 7 00 50	9.32 7 00 50	10.0 00 50	10.0 50	9.27 4 8	10.19 8	9.695 5	9.05 5
MO D_U PI_G R	11.0 91 49 88 70	10.1 49 88 70	10.4 88 70	10.7 70	10.63 0 36	11.1 36	9.95 0 9	9.89 9 00	11.0 00	10.53 6 0	10.44 0	9.84 9
MO D_U PI_F D	11.2 69 9 63 76	9.84 9 63 76	10.8 63 76	11.5 76	11.70 5 45	11.0 45	9.84 9 5	9.69 5 80	11.1 80	10.72 4 4	10.34 4	10.5 36
MO D_U PI_T RVL	9.69 5 00 4 5	10.1 00 4 5	9.64 4 5	8.77 5	9.381 7 2 50	9.74 7 2 50	9.59 2 50	10.0 50	9.48 7	9.899 7	9.592	8.60 2
MO D_U PI_F ASH ION	10.1 49 9 9 1	9.84 9 9 1	9.89 9 1	9.38 1	9.539 00 7 98	10.1 00 7 98	9.74 7 98	10.1 98	9.64 4 0	10.63 0	9.747	8.88 8
MO D_U PI_O thers	9.64 4 4 1 2	9.64 4 4 1 2	9.38 1 2	8.60 2	9.110 4 4 8 5	8.94 4 4 8 5	9.64 4 4 8 5	9.79 8 5	8.77 5	9.434	10.14 9	9.00 0

MO	9.74	9.95	9.79	9.05	9.644	9.05	10.2	10.1	9.64	9.747	9.434	9.43
D_B	7	0	8	5		5	47	00	4			4
NPL												
_EL												
EC												
MO	9.00	10.1	8.36	7.07	7.550	8.12	9.53	10.1	8.18	9.327	9.747	7.93
D_B	0	49	7	1		4	9	00	5			7
NPL												
_GR												
MO	9.43	9.95	8.36	7.34	8.185	8.00	9.74	9.89	8.54	9.110	9.644	8.30
D_B	4	0	7	8		0	7	9	4			7
NPL												
_FD												
MO	9.05	10.0	7.28	6.55	7.483	8.42	8.71	9.64	8.00	9.055	9.381	7.87
D_B	5	00	0	7		6	8	4	0			4
NPL												
_TR												
VL												
MO	9.16	10.0	8.30	7.41	7.874	8.66	9.27	10.0	8.48	9.274	9.381	8.60
D_B	5	00	7	6		0	4	50	5			2
NPL												
_Fas												
hion												
MO	10.2	10.0	10.0	10.1	9.539	10.4	9.43	10.1	9.74	10.05	10.44	10.2
D_B	47	50	00	98		88	4	00	7	0	0	47

NPL _Oth ers												
VAL UE_ COD _LT1 00	0.00 0	11.9 16	10.1 49	8.54 4	8.000	8.30 7	10.0 00	10.1 49	7.61 6	10.00 0	9.381	9.79 8
VAL UE_ COD _100 _1K	11.9 16	0.00 0	11.0 00	10.4 40	10.48 8	10.1 49	9.16 5	9.95 0	10.1 98	9.381	9.798	10.1 98
VAL UE_ COD _1K_ 20K	10.1 49	11.0 00	0.00 0	7.61 6	8.426	8.83 2	9.64 4	9.48 7	8.42 6	9.327	9.644	8.06 2
VAL UE_ COD _GT 20K	8.54 4	10.4 40	7.61 6	0.00 0	7.000	8.12 4	9.43 4	9.05 5	7.14 1	8.888	9.327	6.55 7
VAL UE_ COD _GT 20K	8.00 0	10.4 88	8.42 6	7.00 0	0.000	8.77 5	10.3 92	10.5 36	6.92 8	9.381	9.798	8.60 2

CC_ LT10 0												
VAL	8.30	10.1	8.83	8.12	8.775	0.00	9.53	10.1	7.68	7.810	9.950	9.43
UE_ CC_ 100_ 1K	7	49	2	4		0	9	98	1			4
VAL	10.0	9.16	9.64	9.43	10.39	9.53	0.00	10.3	9.05	9.381	8.832	9.59
UE_ CC_ 1K_2 0K	00	5	4	4	2	9	0	44	5			2
VAL	10.1	9.95	9.48	9.05	10.53	10.1	10.3	0.00	9.53	9.950	9.644	8.30
UE_ CC_ GT2 0K	49	0	7	5	6	98	44	0	9			7
VAL	7.61	10.1	8.42	7.14	6.928	7.68	9.05	9.53	0.00	9.695	10.29	8.83
UE_ DCI B_L T100	6	98	6	1		1	5	9	0		6	2
VAL	10.0	9.38	9.32	8.88	9.381	7.81	9.38	9.95	9.69	0.000	10.39	10.1
UE_ 0K	00	1	7	8		0	1	0	5		2	98

TRV L												
MO D_C OD_ Fashi on	9.00 0	10.0 00	9.84 9	8.83 2	9.644	9.95 0	9.64 4	8.24 6	10.0 00	9.539	9.220	8.83 2
MO D_C OD_ Other s	9.32 7	10.1 00	10.3 44	9.79 8	9.849	10.5 36	9.32 7	9.48 7	9.79 8	9.950	9.220	9.38 1
MO D_C C_E LEC	11.0 91	10.5 83	11.0 00	10.6 77	10.72 4	10.2 47	11.6 19	11.3 14	10.2 96	11.09 1	11.44 6	11.8 32
MO D_C C_G R	9.48 7	10.3 44	10.0 00	9.64 4	10.00 0	10.2 96	10.0 00	9.74 7	10.2 47	10.00 0	10.00 0	10.0 50
MO D_C C_F D	9.16 5	9.95 0	10.1 00	9.32 7	10.19 8	10.3 92	9.79 8	9.22 0	10.2 47	9.487	10.10 0	9.84 9

MO	9.64	9.69	10.6	9.69	10.14	10.3	10.1	10.1	9.89	10.24	10.81	10.4
D_C	4	5	30	5	9	44	49	98	9	7	7	88
C_T												
RVL												
MO	9.74	10.0	10.3	9.16	10.34	9.74	10.1	9.89	9.59	10.34	10.63	10.2
D_C	7	00	44	5	4	7	49	9	2	4	0	96
C_F												
ASH												
ION												
MO	8.71	9.74	9.48	9.53	9.487	10.1	8.94	8.54	9.74	9.381	9.274	8.77
D_C	8	7	7	9		98	4	4	7			5
C_Ot												
hers												
MO	9.43	10.3	10.2	8.36	10.63	10.0	8.88	8.12	10.5	9.539	8.888	8.48
D_D	4	92	47	7	0	50	8	4	83			5
CIB_												
ELE												
C												
MO	10.8	10.3	10.3	9.89	10.63	10.8	9.43	10.3	10.9	10.24	10.24	10.2
D_D	17	92	44	9	0	17	4	92	54	7	7	96
CIB_												
GR												
MO	10.0	10.4	9.64	8.60	10.44	10.3	9.00	8.83	10.4	9.747	9.434	9.27
D_D	50	88	4	2	0	44	0	2	88			4

CIB_ FD												
MO D_D CIB_ TRV L	9.38 1 49	10.1 49	9.89 9	8.88 8	10.19 8	9.79 8	9.05 5	8.66 0	10.5 36	9.274	8.944	9.00 0
MO D_D CIB_ FAS HIO M	9.27 4 49	10.1 49	9.69 5	8.42 6	10.29 6	10.0 00	8.71 8	8.06 2	10.5 36	9.055	8.944	8.54 4
MO D_D CIB_ Other s	8.77 5 00	10.0 00	10.1 49	9.38 1	9.644	9.95 0	9.43 4	9.05 5	10.1 00	9.220	9.220	9.05 5
MO D_U PI_E LEC	9.38 1 49	10.1 49	9.69 5	8.30 7	10.10 0	10.0 00	9.69 5	8.77 5	10.4 40	9.381	8.602	9.11 0
MO D_U	11.0 00	9.89 9	9.43 4	10.0 00	9.950	11.0 00	10.3 44	10.5 83	10.3 92	10.72 4	10.53 6	10.5 83

PI_G R												
MO D_U PI_F D	11.0 00	10.1 00	10.1 49	10.2 96	10.90 9	9.95 0	10.9 09	11.3 14	9.59 2	11.18 0	11.44 6	11.4 02
MO D_U PI_T RVL	9.69 5	10.4 40	9.05 5	8.30 7	10.29 6	10.3 92	9.05 5	8.66 0	10.5 36	9.487	8.944	8.77 5
MO D_U PI_F ASH ION	9.53 9	10.5 83	9.64 4	8.83 2	10.24 7	10.4 40	9.53 9	9.48 7	10.2 96	9.950	9.644	9.59 2
MO D_U PI_O thers	8.77 5	10.1 98	10.4 40	8.83 2	9.747	9.64 4	9.43 4	8.60 2	10.3 92	8.888	8.888	8.71 8
MO D_D W_E LEC	9.43 4	10.0 00	9.95 0	8.60 2	10.72 4	9.84 9	8.42 6	7.74 6	10.9 54	8.888	7.810	8.36 7
MO D_D	9.59 2	9.74 7	9.69 5	8.77 5	10.39 2	9.89 9	8.48 5	8.54 4	10.7 24	8.485	8.944	9.00 0

MO	8.54	9.79	9.53	8.00	10.05	9.53	7.81	6.92	10.7	8.062	7.000	7.21
D_B	4	8	9	0	0	9	0	8	70			1
NPL												
_GR												
MO	8.77	9.79	9.43	7.87	10.44	9.74	7.68	6.92	10.5	8.062	7.550	7.61
D_B	5	8	4	4	0	7	1	8	83			6
NPL												
_FD												
MO	8.12	9.53	9.38	7.81	9.695	9.69	7.48	6.40	10.4	8.124	6.633	6.55
D_B	4	9	1	0		5	3	3	40			7
NPL												
_TR												
VL												
MO	8.71	9.95	9.69	7.81	10.29	9.59	8.00	7.55	10.7	8.367	7.616	7.55
D_B	8	0	5	0	6	2	0	0	24			0
NPL												
_Fas												
hion												
MO	9.32	10.2	9.74	10.4	9.434	10.0	10.1	10.4	9.38	10.72	10.34	10.1
D_B	7	96	7	88		50	49	88	1	4	4	98
NPL												
_Oth												
ers												
VAL	8.48	9.95	10.1	9.43	8.246	10.4	9.38	8.77	9.64	9.165	8.602	8.66
UE_	5	0	98	4		88	1	5	4			0

COD _LT1 00												
VAL UE_ COD _100 _1K	9.48 7	9.11 0	9.89 9	10.5 36	10.00 0	9.16 5	10.0 00	10.4 40	10.4 40	9.592	10.10 0	10.1 49
VAL UE_ COD _1K_ 20K	8.88 8	10.1 00	9.32 7	8.36 7	9.950	9.74 7	7.55 0	7.48 3	10.2 96	8.775	7.550	7.61 6
VAL UE_ COD _GT 20K	7.55 0	9.89 9	9.74 7	6.63 3	9.747	9.53 9	7.28 0	4.24 3	10.1 98	8.185	6.856	4.89 9
VAL UE_ CC_ LT10 0	7.61 6	10.3 44	9.48 7	8.42 6	8.602	10.4 88	8.36 7	7.00 0	9.32 7	9.055	7.874	7.41 6
VAL UE_ UE_ UE_	8.30 7	8.12 4	9.53 9	8.60 2	9.747	8.54 4	8.66 0	8.12 4	10.8 63	7.280	8.185	8.12 4

CC_100_1K												
VAL	8.24	8.77	8.83	9.95	9.487	9.38	8.60	9.64	9.95	9.487	8.718	9.64
UE_	6	5	2	0		1	2	4	0			4
CC_1K_20K												
VAL	9.00	9.69	10.2	8.48	9.434	9.95	9.53	8.60	9.48	10.34	10.05	8.60
UE_	0	5	47	5		0	9	2	7	4	0	2
CC_GT20K												
VAL	6.63	9.84	9.59	8.42	8.246	10.0	8.36	7.28	9.11	8.832	8.246	7.41
UE_	3	9	2	6		00	7	0	0			6
DCI_B_L_T100												
VAL	8.83	8.42	9.38	9.84	10.00	8.48	8.94	9.11	11.0	7.746	9.055	9.11
UE_	2	6	1	9	0	5	4	0	00			0
DCI_B_100_1K												
VAL	9.69	9.22	9.05	9.64	10.10	9.27	8.48	9.74	9.84	10.00	9.165	9.64
UE_	5	0	5	4	0	4	5	7	9	0		4

Table 59: Hierarchical Clustering- Average Linkage

Average Linkage (Between Groups)						
Agglomeration Schedule						
Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	40	56	4.243	0	0	2
2	40	60	4.999	1	0	12
3	32	33	5.657	0	0	5
4	19	22	5.657	0	0	8
5	32	34	5.916	3	0	10
6	28	29	6.245	0	0	14
7	8	9	6.481	0	0	22
8	19	23	6.541	4	0	38
9	48	52	6.557	0	0	12
10	4	32	6.617	0	5	15
11	45	49	6.633	0	0	19
12	40	48	6.647	2	9	26
13	18	30	6.708	0	0	25
14	17	28	6.733	0	6	18
15	4	35	6.848	10	0	18
16	55	59	6.928	0	0	23
17	10	11	6.928	0	0	22
18	4	17	7.245	15	14	21
19	41	45	7.272	0	11	31
20	42	58	7.280	0	0	27

21	4	25	7.371	18	0	28
22	8	10	7.547	7	17	49
23	39	55	7.550	0	16	26
24	15	27	7.550	0	0	29
25	18	24	7.574	13	0	35
26	39	40	7.649	23	12	28
27	42	46	7.778	20	0	37
28	4	39	7.855	21	26	40
29	13	15	7.901	0	24	36
30	2	3	7.937	0	0	34
31	37	41	8.034	0	19	46
32	16	26	8.124	0	0	36
33	53	57	8.185	0	0	46
34	2	5	8.275	30	0	43
35	12	18	8.284	0	25	41
36	13	16	8.322	29	32	38
37	42	50	8.325	27	0	42
38	13	19	8.426	36	8	40
39	20	21	8.485	0	0	51
40	4	13	8.506	28	38	43
41	6	12	8.570	0	35	44
42	42	54	8.572	37	0	54
43	2	4	8.694	34	40	48
44	6	36	8.695	41	0	52
45	43	51	8.832	0	0	47

46	37	53	8.898	31	33	52
47	43	47	8.944	45	0	58
48	2	31	8.991	43	0	50
49	7	8	9.019	0	22	53
50	1	2	9.265	0	48	55
51	14	20	9.274	0	39	56
52	6	37	9.327	44	46	55
53	7	44	9.353	49	0	56
54	38	42	9.479	0	42	57
55	1	6	9.493	50	52	57
56	7	14	9.567	53	51	59
57	1	38	9.661	55	54	58
58	1	43	9.776	57	47	59

Appendix 6: Path Coefficient Table

Table 60: Path Coefficient Table

Inner Model	Path Co-efficient	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AOT -> Freq_BNPL	0.274	0.280	0.098	2.780	0.005
AOT -> Freq_CC	0.065	0.070	0.082	0.790	0.429

AOT -> Freq_COD	0.017	0.015	0.117	0.142	0.88 7
AOT -> Freq_DCIB	-0.013	-0.027	0.118	0.109	0.91 3
AOT -> Freq_DW	0.161	0.158	0.106	1.527	0.12 7
AOT -> Freq_UPI	0.019	0.022	0.106	0.183	0.85 5
AOT -> Payment Preference	0.187	0.189	0.109	1.717	0.08 6
AOT -> SBE	-0.084	-0.068	0.079	1.060	0.28 9
Age -> Freq_BNPL	-0.067	-0.058	0.096	0.692	0.48 9
Age -> Freq_CC	0.043	0.045	0.102	0.423	0.67 2
Age -> Freq_DCIB	0.070	0.065	0.078	0.899	0.36 8
Age -> Freq_DW	-0.006	-0.010	0.084	0.067	0.94 6
Age -> Freq_UPI	-0.064	-0.054	0.161	0.397	0.69 2
Age -> SBE	-0.044	-0.054	0.063	0.689	0.49 1
EE -> PE	0.368	0.371	0.070	5.236	0.00

					0
EE -> SBE	0.129	0.112	0.096	1.350	0.17 7
EFC-1 -> Freq_BNPL	-0.225	-0.233	0.073	3.095	0.00 2
EFC-1 -> Freq_CC	-0.014	-0.020	0.080	0.170	0.86 5
EFC-1 -> Freq_COD	0.041	0.045	0.103	0.397	0.69 1
EFC-1 -> Freq_DCIB	0.012	0.025	0.109	0.112	0.91 1
EFC-1 -> Freq_DW	-0.120	-0.133	0.086	1.394	0.16 3
EFC-1 -> Freq_UPI	-0.003	0.002	0.109	0.031	0.97 5
EFC-1 -> Payment Preference	0.082	0.101	0.098	0.840	0.40 1
EFC-1 -> SBE	-0.088	-0.077	0.072	1.235	0.21 7
EFC-2 -> Freq_BNPL	-0.142	-0.139	0.075	1.900	0.05 7
EFC-2 -> Freq_CC	0.050	0.046	0.073	0.681	0.49 6
EFC-2 -> Freq_COD	0.087	0.084	0.094	0.925	0.35 5

EFC-2 -> Freq_DCIB	-0.019	-0.028	0.092	0.209	0.83 4
EFC-2 -> Freq_DW	-0.043	-0.038	0.084	0.508	0.61 1
EFC-2 -> Freq_UPI	-0.012	-0.010	0.109	0.110	0.91 3
EFC-2 -> Payment Preference	0.273	0.255	0.098	2.793	0.00 5
EFC-2 -> SBE	-0.036	-0.044	0.062	0.579	0.56 2
FC -> HM	0.224	0.226	0.059	3.787	0.00 0
FC -> SBE	0.231	0.221	0.077	2.981	0.00 3
Gender -> Freq_BNPL	-0.110	-0.103	0.077	1.437	0.15 1
Gender -> Freq_CC	0.046	0.041	0.089	0.521	0.60 2
Gender -> Freq_DCIB	0.137	0.134	0.074	1.857	0.06 3
Gender -> Freq_DW	-0.043	-0.046	0.080	0.537	0.59 2
Gender -> Freq_UPI	0.062	0.068	0.107	0.576	0.56 4
Gender -> SBE	0.000	0.002	0.050	0.001	1.00

					0
HM -> SBE	0.030	0.055	0.094	0.317	0.75 2
Income -> Freq_BNPL	-0.066	-0.063	0.076	0.872	0.38 3
Income -> Freq_CC	0.211	0.205	0.105	2.004	0.04 5
Income -> Freq_DCIB	0.067	0.063	0.082	0.818	0.41 3
Income -> Freq_DW	0.125	0.130	0.085	1.469	0.14 2
Income -> Freq_UPI	0.093	0.087	0.133	0.704	0.48 2
Income -> SBE	0.001	-0.008	0.064	0.020	0.98 4
MOD_BNPL_-> Freq_BNPL	0.446	0.481	0.239	1.864	0.06 2
MOD_CC-> Freq_CC	0.789	0.801	0.129	6.132	0.00 0
MOD_DW_-> Freq_DW	0.180	0.176	0.160	1.125	0.26 1
MOD_UPI-> Freq_UPI	0.399	0.422	0.152	2.635	0.00 8
PE -> SBE	0.250	0.239	0.093	2.697	0.00 7

Payment Preference -> EE	0.463	0.466	0.074	6.290	0.00 0
Payment Preference -> FC	0.390	0.393	0.083	4.692	0.00 0
Payment Preference -> Freq_BNPL	0.009	0.016	0.105	0.088	0.93 0
Payment Preference -> Freq_CC	-0.186	-0.180	0.085	2.181	0.02 9
Payment Preference -> Freq_COD	0.112	0.111	0.101	1.110	0.26 7
Payment Preference -> Freq_DCIB	-0.027	-0.031	0.101	0.272	0.78 6
Payment Preference -> Freq_DW	0.042	0.033	0.098	0.424	0.67 1
Payment Preference -> Freq_UPI	-0.006	-0.006	0.104	0.058	0.95 4
Payment Preference -> HM	0.531	0.533	0.060	8.885	0.00 0
Payment Preference -> PE	0.288	0.288	0.073	3.967	0.00 0
Payment Preference -> SBE	0.222	0.207	0.086	2.584	0.01 0
Payment Preference -> SI	0.555	0.559	0.044	12.627	0.00 0
Payment Preference ->	0.467	0.474	0.068	6.842	0.00

Trust					0
Pricing -> Freq_BNPL	-0.063	-0.056	0.093	0.682	0.49 5
Pricing -> Freq_CC	-0.018	-0.017	0.072	0.251	0.80 2
Pricing -> Freq_COD	-0.032	-0.034	0.100	0.322	0.74 7
Pricing -> Freq_DCIB	-0.015	-0.002	0.103	0.143	0.88 6
Pricing -> Freq_DW	-0.087	-0.071	0.109	0.802	0.42 3
Pricing -> Freq_UPI	0.041	0.030	0.098	0.420	0.67 5
Pricing -> Payment Preference	0.135	0.143	0.125	1.075	0.28 2
Pricing -> SBE	0.207	0.188	0.076	2.717	0.00 7
SBE -> Freq_BNPL	0.049	0.041	0.112	0.439	0.66 1
SBE -> Freq_CC	-0.055	-0.055	0.078	0.707	0.48 0
SBE -> Freq_COD	-0.141	-0.136	0.105	1.336	0.18 2
SBE -> Freq_DCIB	0.094	0.091	0.101	0.926	0.35 4

SBE -> Freq_DW	-0.031	-0.023	0.106	0.289	0.77 3
SBE -> Freq_UPI	-0.106	-0.108	0.085	1.249	0.21 2
SI -> EE	0.207	0.208	0.068	3.070	0.00 2
SI -> FC	0.210	0.209	0.074	2.848	0.00 4
SI -> SBE	-0.131	-0.113	0.075	1.742	0.08 2
Trust -> PE	0.205	0.202	0.077	2.673	0.00 8
Trust -> SBE	0.293	0.268	0.071	4.130	0.00 0
VALUE_GT20 -> Freq_DCIB	1.049	1.062	0.221	4.740	0.00 0
VALUE_GT20 -> Freq_DW	0.823	0.828	0.258	3.190	0.00 1
VALUE_GT20 -> Freq_UPI	0.368	0.366	0.268	1.374	0.16 9
Gender x HM -> SBE	0.031	0.018	0.082	0.385	0.70 0
Gender x PE -> SBE	0.102	0.099	0.104	0.980	0.32 7
Age x VALUE_GT20 ->	-0.214	-0.197	0.264	0.809	0.41

Freq_DCIB					8
Age x VALUE_GT20 -> Freq_DW	0.492	0.450	0.296	1.662	0.09 7
Age x VALUE_GT20 -> Freq_UPI	0.259	0.257	0.253	1.022	0.30 7
Income x SI -> SBE	-0.025	-0.028	0.078	0.323	0.74 7
Gender x MOD_CC -> Freq_CC	-0.107	-0.099	0.145	0.738	0.46 0
Gender x EE -> SBE	-0.030	-0.012	0.091	0.334	0.73 8
Income x VALUE_GT20 -> Freq_DCIB	0.020	-0.010	0.240	0.081	0.93 5
Income x VALUE_GT20 -> Freq_DW	-0.050	-0.070	0.280	0.180	0.85 7
Income x VALUE_GT20 -> Freq_UPI	-0.098	-0.115	0.283	0.347	0.72 9
Income x HM -> SBE	0.067	0.060	0.095	0.711	0.47 7
Gender x SI -> SBE	-0.056	-0.051	0.066	0.849	0.39 6
Age x MOD_CC -> Freq_CC	0.126	0.128	0.151	0.833	0.40 5
Gender x MOD_DW_ -> Freq_DW	0.424	0.432	0.185	2.299	0.02 2

Age x SI -> SBE	-0.027	-0.030	0.089	0.302	0.76 3
Age x Trust -> SBE	0.021	0.033	0.079	0.270	0.78 7
Income x MOD_BNPL_ -> Freq_BNPL	0.236	0.209	0.251	0.937	0.34 9
Age x PE -> SBE	0.091	0.118	0.109	0.832	0.40 6
Gender x VALUE_GT20 -> Freq_DCIB	0.128	0.117	0.301	0.426	0.67 0
Gender x VALUE_GT20 -> Freq_DW	0.102	0.107	0.345	0.297	0.76 6
Gender x VALUE_GT20 -> Freq_UPI	-0.256	-0.276	0.365	0.703	0.48 2
Income x PE -> SBE	0.161	0.117	0.107	1.505	0.13 2
Age x MOD_DW_ -> Freq_DW	-0.169	-0.143	0.223	0.754	0.45 1
Income x FC -> SBE	0.089	0.076	0.073	1.220	0.22 3
Income x EE -> SBE	-0.266	-0.238	0.123	2.162	0.03 1
Gender x MOD_UPI -> Freq_UPI	0.051	0.046	0.163	0.316	0.75 2
Income x MOD_UPI ->	0.075	0.075	0.205	0.366	0.71

Freq_UPI					4
Gender x MOD_BNPL_ -> Freq_BNPL	0.350	0.319	0.225	1.556	0.12 0
Age x FC -> SBE	0.075	0.075	0.072	1.037	0.30 0
Age x MOD_BNPL_ -> Freq_BNPL	0.132	0.131	0.226	0.585	0.55 9
Income x MOD_CC -> Freq_CC	-0.029	-0.024	0.135	0.215	0.83 0
Gender x FC -> SBE	-0.050	-0.062	0.075	0.661	0.50 8
Age x EE -> SBE	0.158	0.118	0.108	1.461	0.14 4
Age x MOD_UPI -> Freq_UPI	-0.093	-0.100	0.185	0.502	0.61 6
Age x HM -> SBE	-0.246	-0.249	0.106	2.329	0.02 0
Income x MOD_DW_ -> Freq_DW	0.304	0.311	0.182	1.669	0.09 5

Total Effect:

Table 61: Total Effect

Factors	Total effects
AOT -> EE	0.108
AOT -> FC	0.095

AOT -> Freq_BNPL	0.277
AOT -> Freq_CC	0.029
AOT -> Freq_COD	0.034
AOT -> Freq_DCIB	-0.015
AOT -> Freq_DW	0.168
AOT -> Freq_UPI	0.015
AOT -> HM	0.120
AOT -> PE	0.112
AOT -> Payment Preference	0.187
AOT -> SBE	0.028
AOT -> SI	0.104
AOT -> Trust	0.087
Age -> Freq_BNPL	-0.069
Age -> Freq_CC	0.045
Age -> Freq_COD	0.006
Age -> Freq_DCIB	0.066
Age -> Freq_DW	-0.004
Age -> Freq_UPI	-0.059
Age -> SBE	-0.045
EE -> Freq_BNPL	0.011
EE -> Freq_CC	-0.012
EE -> Freq_COD	-0.032
EE -> Freq_DCIB	0.021
EE -> Freq_DW	-0.007
EE -> Freq_UPI	-0.024

EE -> PE	0.368
EE -> SBE	0.225
EFC-1 -> EE	0.048
EFC-1 -> FC	0.042
EFC-1 -> Freq_BNPL	-0.225
EFC-1 -> Freq_CC	-0.027
EFC-1 -> Freq_COD	0.054
EFC-1 -> Freq_DCIB	0.007
EFC-1 -> Freq_DW	-0.116
EFC-1 -> Freq_UPI	-0.001
EFC-1 -> HM	0.053
EFC-1 -> PE	0.049
EFC-1 -> Payment Preference	0.082
EFC-1 -> SBE	-0.028
EFC-1 -> SI	0.046
EFC-1 -> Trust	0.038
EFC-2 -> EE	0.158
EFC-2 -> FC	0.138
EFC-2 -> Freq_BNPL	-0.132
EFC-2 -> Freq_CC	-0.009
EFC-2 -> Freq_COD	0.098
EFC-2 -> Freq_DCIB	-0.013
EFC-2 -> Freq_DW	-0.036
EFC-2 -> Freq_UPI	-0.029
EFC-2 -> HM	0.176

EFC-2 -> PE	0.163
EFC-2 -> Payment Preference	0.273
EFC-2 -> SBE	0.141
EFC-2 -> SI	0.151
EFC-2 -> Trust	0.127
FC -> Freq_BNPL	0.012
FC -> Freq_CC	-0.013
FC -> Freq_COD	-0.034
FC -> Freq_DCIB	0.023
FC -> Freq_DW	-0.007
FC -> Freq_UPI	-0.026
FC -> HM	0.224
FC -> SBE	0.244
Gender -> Freq_BNPL	-0.111
Gender -> Freq_CC	0.047
Gender -> Freq_COD	0.000
Gender -> Freq_DCIB	0.137
Gender -> Freq_DW	-0.043
Gender -> Freq_UPI	0.062
Gender -> SBE	-0.003
HM -> Freq_BNPL	0.001
HM -> Freq_CC	-0.001
HM -> Freq_COD	-0.003
HM -> Freq_DCIB	0.002
HM -> Freq_DW	-0.001

HM -> Freq_UPI	-0.002
HM -> SBE	0.019
Income -> Freq_BNPL	-0.066
Income -> Freq_CC	0.211
Income -> Freq_COD	0.000
Income -> Freq_DCIB	0.067
Income -> Freq_DW	0.125
Income -> Freq_UPI	0.093
Income -> SBE	0.000
MOD_BNPL_ -> Freq_BNPL	0.446
MOD_CC -> Freq_CC	0.789
MOD_DW_ -> Freq_DW	0.180
MOD_UPI -> Freq_UPI	0.399
PE -> Freq_BNPL	0.012
PE -> Freq_CC	-0.014
PE -> Freq_COD	-0.035
PE -> Freq_DCIB	0.023
PE -> Freq_DW	-0.008
PE -> Freq_UPI	-0.026
PE -> SBE	0.250
Payment Preference -> EE	0.578
Payment Preference -> FC	0.507
Payment Preference -> Freq_BNPL	0.041
Payment Preference -> Freq_CC	-0.221
Payment Preference -> Freq_COD	0.022

Payment Preference -> Freq_DCIB	0.033
Payment Preference -> Freq_DW	0.022
Payment Preference -> Freq_UPI	-0.074
Payment Preference -> HM	0.644
Payment Preference -> PE	0.597
Payment Preference -> SBE	0.643
Payment Preference -> SI	0.555
Payment Preference -> Trust	0.467
Pricing -> EE	0.078
Pricing -> FC	0.068
Pricing -> Freq_BNPL	-0.048
Pricing -> Freq_CC	-0.059
Pricing -> Freq_COD	-0.058
Pricing -> Freq_DCIB	0.009
Pricing -> Freq_DW	-0.091
Pricing -> Freq_UPI	0.009
Pricing -> HM	0.087
Pricing -> PE	0.080
Pricing -> Payment Preference	0.135
Pricing -> SBE	0.293
Pricing -> SI	0.075
Pricing -> Trust	0.063
SBE -> Freq_BNPL	0.049
SBE -> Freq_CC	-0.055
SBE -> Freq_COD	-0.141

SBE -> Freq_DCIB	0.094
SBE -> Freq_DW	-0.031
SBE -> Freq_UPI	-0.106
SI -> EE	0.207
SI -> FC	0.210
SI -> Freq_BNPL	-0.001
SI -> Freq_CC	0.002
SI -> Freq_COD	0.004
SI -> Freq_DCIB	-0.003
SI -> Freq_DW	0.001
SI -> Freq_UPI	0.003
SI -> HM	0.047
SI -> PE	0.076
SI -> SBE	-0.029
Trust -> Freq_BNPL	0.016
Trust -> Freq_CC	-0.018
Trust -> Freq_COD	-0.047
Trust -> Freq_DCIB	0.031
Trust -> Freq_DW	-0.010
Trust -> Freq_UPI	-0.035
Trust -> PE	0.205
Trust -> SBE	0.331
VALUE_GT20 -> Freq_DCIB	1.049
VALUE_GT20 -> Freq_DW	0.823
VALUE_GT20 -> Freq_UPI	0.368

Gender x HM -> Freq_BNPL	0.000
Gender x HM -> Freq_CC	0.000
Gender x HM -> Freq_COD	0.000
Gender x HM -> Freq_DCIB	0.000
Gender x HM -> Freq_DW	0.000
Gender x HM -> Freq_UPI	0.000
Gender x HM -> SBE	-0.001
Gender x PE -> Freq_BNPL	0.005
Gender x PE -> Freq_CC	-0.005
Gender x PE -> Freq_COD	-0.014
Gender x PE -> Freq_DCIB	0.009
Gender x PE -> Freq_DW	-0.003
Gender x PE -> Freq_UPI	-0.010
Gender x PE -> SBE	0.099
Age x VALUE_GT20 -> Freq_DCIB	-0.214
Age x VALUE_GT20 -> Freq_DW	0.492
Age x VALUE_GT20 -> Freq_UPI	0.259
Income x SI -> Freq_BNPL	-0.001
Income x SI -> Freq_CC	0.001
Income x SI -> Freq_COD	0.001
Income x SI -> Freq_DCIB	-0.001
Income x SI -> Freq_DW	0.000
Income x SI -> Freq_UPI	0.001
Income x SI -> SBE	-0.010
Gender x MOD_CC -> Freq_CC	-0.107

Gender x EE -> Freq_BNPL	-0.002
Gender x EE -> Freq_CC	0.002
Gender x EE -> Freq_COD	0.006
Gender x EE -> Freq_DCIB	-0.004
Gender x EE -> Freq_DW	0.001
Gender x EE -> Freq_UPI	0.005
Gender x EE -> SBE	-0.044
Income x VALUE_GT20 -> Freq_DCIB	0.020
Income x VALUE_GT20 -> Freq_DW	-0.050
Income x VALUE_GT20 -> Freq_UPI	-0.098
Income x HM -> Freq_BNPL	0.004
Income x HM -> Freq_CC	-0.004
Income x HM -> Freq_COD	-0.011
Income x HM -> Freq_DCIB	0.008
Income x HM -> Freq_DW	-0.002
Income x HM -> Freq_UPI	-0.009
Income x HM -> SBE	0.081
Gender x SI -> Freq_BNPL	-0.003
Gender x SI -> Freq_CC	0.004
Gender x SI -> Freq_COD	0.009
Gender x SI -> Freq_DCIB	-0.006
Gender x SI -> Freq_DW	0.002
Gender x SI -> Freq_UPI	0.007
Gender x SI -> SBE	-0.066

Age x MOD_CC -> Freq_CC	0.126
Gender x MOD_DW_ -> Freq_DW	0.424
Age x SI -> Freq_BNPL	-0.002
Age x SI -> Freq_CC	0.002
Age x SI -> Freq_COD	0.005
Age x SI -> Freq_DCIB	-0.003
Age x SI -> Freq_DW	0.001
Age x SI -> Freq_UPI	0.004
Age x SI -> SBE	-0.034
Age x Trust -> Freq_BNPL	0.001
Age x Trust -> Freq_CC	-0.001
Age x Trust -> Freq_COD	-0.004
Age x Trust -> Freq_DCIB	0.002
Age x Trust -> Freq_DW	-0.001
Age x Trust -> Freq_UPI	-0.003
Age x Trust -> SBE	0.027
Income x MOD_BNPL_ -> Freq_BNPL	0.236
Age x PE -> Freq_BNPL	0.005
Age x PE -> Freq_CC	-0.006
Age x PE -> Freq_COD	-0.014
Age x PE -> Freq_DCIB	0.010
Age x PE -> Freq_DW	-0.003
Age x PE -> Freq_UPI	-0.011
Age x PE -> SBE	0.101

Gender x VALUE_GT20 -> Freq_DCIB	0.128
Gender x VALUE_GT20 -> Freq_DW	0.102
Gender x VALUE_GT20 -> Freq_UPI	-0.256
Income x PE -> Freq_BNPL	0.007
Income x PE -> Freq_CC	-0.008
Income x PE -> Freq_COD	-0.020
Income x PE -> Freq_DCIB	0.014
Income x PE -> Freq_DW	-0.004
Income x PE -> Freq_UPI	-0.015
Income x PE -> SBE	0.145
Age x MOD_DW_ -> Freq_DW	-0.169
Income x FC -> Freq_BNPL	0.004
Income x FC -> Freq_CC	-0.005
Income x FC -> Freq_COD	-0.012
Income x FC -> Freq_DCIB	0.008
Income x FC -> Freq_DW	-0.003
Income x FC -> Freq_UPI	-0.009
Income x FC -> SBE	0.088
Income x EE -> Freq_BNPL	-0.012
Income x EE -> Freq_CC	0.013
Income x EE -> Freq_COD	0.034
Income x EE -> Freq_DCIB	-0.023
Income x EE -> Freq_DW	0.007
Income x EE -> Freq_UPI	0.026

Income x EE -> SBE	-0.243
Gender x MOD_UPI -> Freq_UPI	0.051
Income x MOD_UPI -> Freq_UPI	0.075
Gender x MOD_BNPL_ -> Freq_BNPL	0.350
Age x FC -> Freq_BNPL	0.003
Age x FC -> Freq_CC	-0.004
Age x FC -> Freq_COD	-0.010
Age x FC -> Freq_DCIB	0.006
Age x FC -> Freq_DW	-0.002
Age x FC -> Freq_UPI	-0.007
Age x FC -> SBE	0.069
Age x MOD_BNPL_ -> Freq_BNPL	0.132
Income x MOD_CC -> Freq_CC	-0.029
Gender x FC -> Freq_BNPL	-0.003
Gender x FC -> Freq_CC	0.003
Gender x FC -> Freq_COD	0.007
Gender x FC -> Freq_DCIB	-0.005
Gender x FC -> Freq_DW	0.002
Gender x FC -> Freq_UPI	0.005
Gender x FC -> SBE	-0.051
Age x EE -> Freq_BNPL	0.007
Age x EE -> Freq_CC	-0.008
Age x EE -> Freq_COD	-0.021
Age x EE -> Freq_DCIB	0.014

Age x EE -> Freq_DW	-0.005
Age x EE -> Freq_UPI	-0.016
Age x EE -> SBE	0.151
Age x MOD_UPI -> Freq_UPI	-0.093
Age x HM -> Freq_BNPL	-0.013
Age x HM -> Freq_CC	0.014
Age x HM -> Freq_COD	0.036
Age x HM -> Freq_DCIB	-0.024
Age x HM -> Freq_DW	0.008
Age x HM -> Freq_UPI	0.027
Age x HM -> SBE	-0.259
Income x MOD_DW_ -> Freq_DW	0.304
Gender x Payment Preference -> Freq_BNPL	0.003
Gender x Payment Preference -> Freq_CC	-0.004
Gender x Payment Preference -> Freq_COD	-0.009
Gender x Payment Preference -> Freq_DCIB	0.006
Gender x Payment Preference -> Freq_DW	-0.002
Gender x Payment Preference -> Freq_UPI	-0.007
Gender x Payment Preference -> SBE	0.067

Age x Payment Preference -> Freq_BNPL	0.001
Age x Payment Preference -> Freq_CC	-0.001
Age x Payment Preference -> Freq_COD	-0.003
Age x Payment Preference -> Freq_DCIB	0.002
Age x Payment Preference -> Freq_DW	-0.001
Age x Payment Preference -> Freq_UPI	-0.002
Age x Payment Preference -> SBE	0.023
Income x Payment Preference -> Freq_BNPL	-0.002
Income x Payment Preference -> Freq_CC	0.003
Income x Payment Preference -> Freq_COD	0.007
Income x Payment Preference -> Freq_DCIB	-0.005
Income x Payment Preference -> Freq_DW	0.001
Income x Payment Preference -> Freq_UPI	0.005

Income x Payment Preference -> SBE	-0.048
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² Naidoo R. Showing you how to do automatic referencing. Proposal Template. 2008